PHD

Thermal Comfort, Control and Energy Use

Vellei, Marika

Award date:
2017

Awarding institution:
University of Bath

Thermal Comfort, Control and Energy Use

Marika Vellei

A thesis submitted for the Degree of Doctor of Philosophy at:

Bath, September 2017

Centre for Energy and the Design of Environments (EDEn)
Department of Architecture and Civil Engineering
Faculty of Engineering & Design
University of Bath, UK

Thermal Comfort, Control and Energy Use

Supervisors

Dr Sukumar Natarajan	University of Bath
Dr Ian Walker	University of Bath

Examination committee

Prof Marialena Nikolopoulou	University of Kent
Dr Thomas Kjeldsen	University of Bath

This work was financially supported by the University of Bath, through a University Research Scholarship.

"Poi piovve dentro a l'alta fantasia"
D. Alighieri

List of publications

This is a list of journal and conference papers published as part of this thesis work.

Journal Publications:

Albadra, D., **Vellei, M.**, Coley, D., Hart, J., Thermal comfort in desert refugee camps: An interdisciplinary approach, Building and Environment 124: 460-477 (2017).
doi.org/10.1016/j.buildenv.2017.08.016

Vellei, M., Herrera, M., Fosas, D., Natarajan, S., The influence of relative humidity on adaptive thermal comfort, Building and Environment 124: 171-185 (2017).
doi.org/10.1016/j.buildenv.2017.08.005

Coley, D., Herrera, M., Fosas, D., Liu, C., **Vellei, M.**, Probabilistic adaptive thermal comfort for resilient design, Building and Environment 123: 109-118 (2017).
doi.org/10.1016/j.buildenv.2017.06.050

Vellei, M., Ramallo-González, A.P., Coley, D., Gabe-Thomas, E., Lee, J., Lovett, T., Natarajan, S., Overheating in vulnerable and non-vulnerable households, Building Research & Information 45: 102-118 (2017).
doi:10.1080/09613218.2016.1222190

Vellei, M., Natarajan, S., Biri, B., Padget, J., Walker, I., The effect of real-time context-aware feedback on occupants' heating behaviour and thermal adaptation, Energy and Buildings 123: 179-191 (2016).
doi:10.1016/j.enbuild.2016.03.045

Williams, J., et *al.*, Less is more: A review of low energy standards and the urgent need for an international universal zero energy standard, Journal of Building Engineering 6: 65-74 (2016).
doi:10.1016/j.jobe.2016.02.007

Natarajan, S., Rodriguez, J., **Vellei, M.**, A field study of indoor thermal comfort in the subtropical highland climate of Bogotá, Colombia, Journal of Building Engineering 4: 237-246 (2015).
doi:10.1016/j.jobe.2015.10.003

Conference Proceedings:

Vellei, M., Zhang, M., Lee, B.J., Natarajan, S., Effect of a moderately warm environment on salivary cortisol level, Healthy Buildings 2017 Europe, Lublin, Poland, 2017.

Vellei, M., Ramallo-González, A.P., Kaleli, D., Lee, J., Natarajan, S., Investigating the overheating risk in refurbished social housing, 9th Windsor Conference 2016 - MAKING COMFORT RELEVANT, Cumberland Lodge, Windsor Great Park, UK, 2016.

Vellei, M., Natarajan, S., Biri, B., Padget, J., Walker, I., The effect of real-time context-aware feedback on thermal comfort and heating energy use: A case study, 31th International PLEA Conference - ARCHITECTURE IN (R)EVOLUTION, Bologna, Italy, 2015.

Ramallo-González, A.P., **Vellei, M.**, Brown, M., Coley, D., Remote façade surveying of windows characteristics, Energy Procedia 78: 925-930 (2015).
doi:10.1016/j.egypro.2015.11.020

Contents

List of Tables

List of Figures

Summary

The theory of adaptive thermal comfort has radically changed our understanding of thermal comfort and its application in naturally ventilated and hence more sustainable buildings. Field studies have allowed to consider psychological and behavioural aspects, which were ignored in the traditional PMV/PPD model. The models derived from the adaptive theory (EN 15251 and ASHRAE-55) provide practitioners with a linear relationship relating indoor comfort temperatures with outdoor temperatures, which has the advantage of being easily understandable and applicable. However, a number of limitations exist in both the theory and application of the adaptive hypothesis. In this thesis, we identify these limitations and address them. Firstly, the current models reduce the adaptive hypothesis to a linear relationship between the indoor comfort temperatures and the outdoor temperatures, hence excluding all other variables. This seems to militate against the well-known physiological impacts of variables such as air humidity and air velocity. Using global thermal comfort field data, this thesis demonstrates for the first time that air humidity has a significant effect on occupant thermal perception. This result is then cast into a new model of adaptive comfort that allows practitioners to design naturally ventilated buildings in a variety of temperature-humidity contexts. Secondly, the traditional adaptive models claim validity over a wide range of geographic and climatic locations, included some from which no empirical data were derived, as well as applicability in a range of building categories (e.g. residential, educational) despite primarily being derived from office buildings. This thesis thus investigates whether the EN 15251 adaptive model, derived principally from data collected in non-UK office buildings, is able to predict thermal comfort of British residential occupants through comparison against field data collected in UK homes. Results demonstrate that the European adaptive model underestimates thermal discomfort of British residential occupants. Finally, this thesis investigates whether perception of control, which is known to affect the adaptive response of occupants, impacts the ability to drive behavioural change through occupant feedback – a major part of the smart meter roll-out across the world. Results from a field study demonstrate that real-time and context-aware feedback could contribute to an increase in occupant perceived environmental control while prompting lower heating energy behaviours.

Acknowledgements

This work would have not been possible without the guidance, encouragement and help of Sukumar. Without his support I would have never had the confidence needed to defend my ideas and carry them on. So the first of all my thanks goes to him.

I need to thank Alfonso, Manuel and Daniel for the stimulating discussions I had with them, their presence and contributions were fundamental in shaping this thesis.

Special thanks to David for his contagious creativity which pushed the boundaries of this thesis in directions that I would have, otherwise, never dared to explore.

I also want to thank Ben, Jeehang, Ian, Julian and Nick for their useful help at various steps of this work.

Without the passion and inspiration of the good teachers that I have met, I would have never reached such a far stage in my education. I really need to thank them all.

On a personal level, these last three years were not always easy but, at the end and like I always do, I will keep with me only the beautiful memories and for these memories I have to thank Mirella, Elisabetta, Eva, Manolis, Sotiris, Erwin, my dance teacher Hannily and, last but not least, my friends in Ascoli.

Without Kevinuccio I would have never survived this PhD so the biggest of all the possible and imaginable thanks to him.

Finally, I think I have never properly thanked my family for supporting my choices, even when they meant being far from home, so this is the chance to officially put it on paper:

Furia grazie famiglia!

Chapter 1

Introduction

1.1 Thermal comfort models and standards

Humans have always strived to achieve a comfortable thermal environment as a fundamental aspect of their survival. But it is only over the last half century that indoor thermal comfort research and standardization have gained global attention and importance. The advent of air-conditioning and the 1970s energy crisis have been fundamental contributors to this growth. On one side, air-conditioning has made it possible to finely control indoor temperatures; on the other side, just as air-conditioning use was soaring in the 1970s, the energy crisis forced the major industrial countries of the world to face the reality of limited available energy resources. As a consequence, thermal comfort research has developed and grown around two main research problems:

- How do we define comfortable indoor thermal environments that can enhance occupant well-being, health and productivity?
- How do we ensure a sustainable design through low heating and cooling energy use in buildings?

The way that scientists have tried to address these two problems has influenced existing thermal comfort models and standards.

1.1.1 Fanger's PMV/PPD model

It is easily demonstrated that the physical environment affects the human thermal response. However, thermal comfort is most often defined as "that condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation" (ASHRAE, 2013), hence thermal comfort is acknowledged as a psychological rather than a physiological state. This definition recognizes that humans are much more than a body mass subject to the laws of thermodynamics; they exist in a psychosocial environment that influences their expectations, emotions, feelings and behaviours, which in turn affect their comfort (Parsons, 2002). This makes thermal comfort a very interdisciplinary field of study, involving physiology, psychology and building physics.

At the dawn of thermal comfort research the focus was mainly on the human physiological response to the surrounding physical environment. In this regard, the most significant contribution to thermal comfort knowledge was given by P.O. Fanger (Parsons, 2002). Fanger first recognized that thermal comfort is the result of the interaction of six basic parameters: air temperature, mean radiant temperature, air movement, air humidity, clothing insulation and metabolic heat generated by human activity. According to Fanger (1970), the body heat balance is a condition necessary but not sufficient to achieve thermal comfort, being also necessary to have a mean skin temperature and a sweat secretion rate within comfort limits which depend on the metabolic activity and are to be determined through experiments in climate chambers.

Fanger's steady-state heat-balance model led to the definition of the well-known PMV (Predicted Mean Vote) and PPD (Predicted Percentage of Dissatisfied) indices which were first incorporated into the ISO international standard in 1984 and, afterwards, in 1992 into the ASHRAE Standard 55, becoming the recognized global indices for thermal comfort.

However, following the introduction and adoption of Fanger's PMV/PPD model, field studies in free-running naturally ventilated buildings have showed significant differences between monitored data and PMV model predictions (Humphreys, 1976; De Dear et al., 1998; Van Hoof, 2008). This has been partly attributed to the difficulties to correctly estimate clothing insulation and metabolic rate (Havenith et al., 2002) and accurately measure air temperatures and air velocities during field studies (Baker and Standeven, 1996). However, according to De Dear et al. (1998) and Nicol and Humphreys (2002), Fanger's model is not able to predict thermal comfort responses in free-running naturally ventilated buildings because it only partially accounts for the adaptive opportunities available to the occupants. The availability and extent of these adaptive opportunities are influenced by different demographical, contextual, social, cultural and cognitive factors. These in turn depend on physical and social attributes of the buildings which are not entirely reproducible and hence are ignored in climate chamber experiments.

The difficulties of Fanger's model to correctly predict comfort in naturally ventilated buildings and the fact that the model influences the design of buildings with strictly-controlled steady-state indoor conditions, hence necessarily relying on air-conditioning, has favoured the adoption of new kinds of thermal comfort models derived from field data and suitable for the design of naturally ventilated and more sustainable buildings.

1.1.2 Adaptive thermal comfort models

An adaptive theory and model of thermal comfort were first introduced by Nicol and Humphreys in the 1970s (Nicol and Humphreys, 1973). However, an adaptive model was for the first time incorporated into the ASHRAE Standard 55 only in 2004, thanks to the research of Brager and de Dear (De Dear et al., 1998).

The adaptive model does not aim to specify an optimum set of indoor environmental variables, unlike Fanger's PMV/PPD model, but rather to define a wide band of indoor temperatures within which occupants can find their own optimum given sufficient adaptive opportunities (Nicol and Humphreys, 1973). One of the main contributions of the adaptive theory is in observing, by analysing field data, that the range of acceptable temperatures in naturally ventilated buildings is larger than in air-conditioned ones and that comfort temperatures are a function of the external air temperatures (Dear et al., 2013). This is due to the fact that occupants can adapt to increasing outdoor temperatures both psychologically and behaviourally. Their adaptations constitute fundamental human reactions to sensations of thermal discomfort (Gagge et al., 1967; Baker and Standeven, 1996).

The ANSI/ASHRAE Standard 55 and the European Standard EN 15251 are the two internationally-used thermal comfort standards that have first adopted an adaptive model and represent the main reference standards for adaptive thermal comfort research.

ASHRAE Standard 55 The ASHRAE Standard 55 is the reference standard for thermal comfort in North America. It has been the first international standard to include an adaptive component. The adaptive component of the standard is based on data collected in the 1990s by de Dear and Brager as part of the ASHRAE Project RP-884 (De Dear et al., 1998) involving more than 21,000 measurements primarily in office buildings in Thailand, Indonesia, Singapore, Pakistan, Greece, the UK, USA, Canada and Australia. De Dear et al. (1998) divided the surveyed buildings in naturally ventilated (NV), centrally heated, ventilated and air-conditioned (HVAC) and mixed-mode (MM). Following the results from those field studies, they observed that the PMV model was able to predict mean thermal sensations in HVAC buildings but did not accurately approximate mean thermal sensations in NV buildings. They also observed a linear relation between indoor comfort temperatures and outdoor temperatures for free-running spaces and derived the following equation for determining acceptable thermal conditions in naturally ventilated buildings:

$$T_{comf} = 0.31 T_{out} + 17.8 \tag{1.1}$$

where T_{comf} is the comfort temperature in °C and T_{out} is the prevailing mean outdoor air temperature in °C which can be approximated by the exponentially weighted running mean temperature T_{rm}:

$$T_{rm} = \Big(1 - \alpha\Big)\Big(T_{-1} + \alpha T_{-2} + \alpha^2 T_{-3} + \dots\Big) \tag{1.2}$$

where T_{-1} is the mean outdoor temperature of the day before the day in question, T_{-2} for the day before that and so on. ASHRAE (2013) suggests using a value for α between 0.6 and 0.9.

The ASHRAE adaptive equation is only valid for summer conditions. ASHRAE (2013) clearly states that there is not specific guidance outside the given boundaries, i.e. for prevailing mean outdoor temperatures $T_{out} \leq 10$°C and $T_{out} \geq 33.5$°C.

There are two comfort bandwidths for 80% and 90% thermal acceptability as shown in Figure 1.1. The first is for typical application while the second is for special application where higher standards of comfort are required.

In particular, ASHRAE (2013) specifies that the adaptive model can be applied to naturally-conditioned spaces where unconditioned mechanical ventilation is allowed, but:

- opening and closing of windows must be the primary means of controlling thermal conditions,
- mechanical cooling systems must not be present,
- heating systems must not be in operation,
- occupants have to be allowed to freely adapt their clothing,
- occupant metabolic rates have to range between 1.0 and 1.3 met (i.e. sedentary activities).

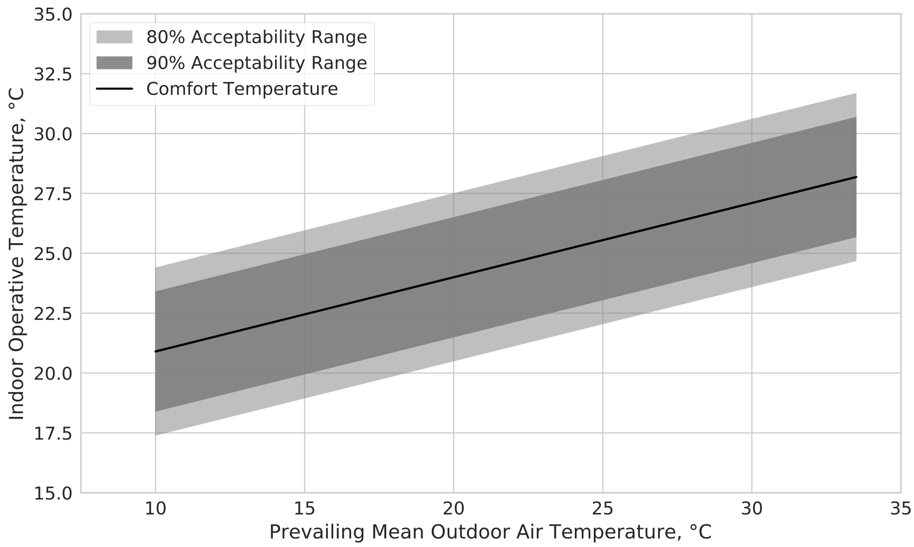


Figure 1.1: Comfort temperature bands for 80% and 90% thermal acceptability for naturally-conditioned spaces. These limits apply for prevailing mean outdoor air temperatures $10 < T_{out} < 33.5$°C. Adapted from: ASHRAE (2013).

European Standard 15251 The European Standard EN 15251 is the standard which deals with both thermal comfort and other indoor environmental parameters in Europe. It was one of the standards designed to support the Energy Performance of Building Directive (EPBD) aimed at reducing the energy use of the European built environment. Since 2007 it contains an adaptive model described by Nicol and Humphreys (2010) and based on data collected in the EU Project Smart Controls and Thermal Comfort (SCATs) which involved year-round surveys of 26 European buildings (free-running, conditioned and mixed-mode) in France, Greece, Portugal, Sweden and the UK. Based on the results from those surveys, Nicol and Humphreys (2010) observed that field findings did not match PMV model predictions and that the range of comfort temperatures in naturally ventilated buildings was much larger than the one predicted by Fanger's PMV/PPD model. They derived the following adaptive equation for naturally ventilated buildings:

$$T_{comf} = 0.33T_{out} + 18.8 \tag{1.3}$$

where T_{comf} is the comfort temperature in °C and T_{out} is, as in the ASHRAE Standard 55, the exponentially weighted running mean of the daily mean outdoor temperature T_{rm} of the previous seven days (when a longer series of days is not available), see Equation 1.2. The value recommended for the constant α is 0.8. Since α is smaller than 1 the relation for T_{out} gives more importance to temperatures of days closer to the time of the survey and less importance to temperatures of more distant days. This is based on the assumption that the past thermal history of a person influences his/her thermal expectations and also takes into account the effect of the building thermal inertia which creates a time lag between outdoor and indoor temperatures (Nicol and Humphreys, 2010). There are four different acceptable temperature ranges according to the three building categories (I, II, III) described in Table 1.1 and shown in Figure 1.2. These categories are intended to divide buildings according to their type rather than their quality (Nicol and Humphreys, 2010).

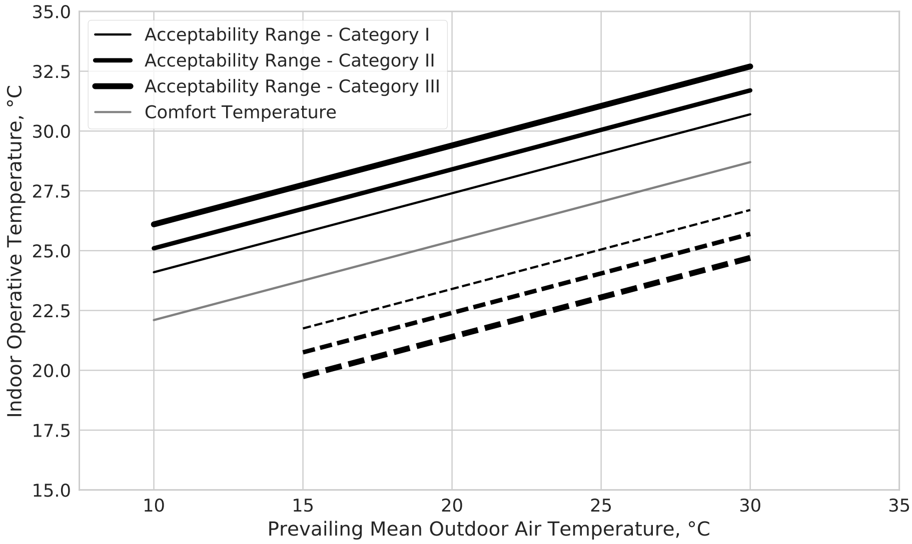


Figure 1.2: Upper (continuous lines) and lower (dashed lines) operative temperature limits for thermal comfort (comfort temperature bands) for free-running spaces according to the three categories I, II, III. These limits apply when $10 < T_{out} < 30$°C for the upper limit and $15 < T_{out} < 30$°C for the lower limit. Adapted from: (EN, 2007).

Table 1.1: Description of the applicability of the categories used in the European Standard EN 15251 (EN, 2007).

Category	Explanation
I	High level of expectation and is recommended for spaces occupied by very sensitive and fragile persons with special requirements like handicapped, sick, very young children and elderly persons.
II	Normal level of expectation and should be used for new buildings and renovations.
III	An acceptable, moderate level of expectation and may be used for existing buildings.

Differences between the ASHRAE and European models The ASHRAE and European models consist of similar linear equations relating indoor comfort temperatures to prevailing outdoor temperatures; this gives general support to their validity. However, they are not directly comparable since some important differences exist:

- They are derived from completely different databases: ASHRAE has a global geographical scope while EN is meant to be only applicable for Europe.
- Their building classification is different: the ASHRAE linear equation cannot be applied to mixed-mode buildings (mechanical cooling systems must not be present) while the EN 15251 model can be applied to any free-running building (no energy should be used for heating or cooling at the time of the survey) with operable windows and relaxed clothing policy.
- The derivation of the neutral temperatures is different: the large ASHRAE database (a total of 21,000 questionnaires) allowed Brager and de Dear to calculate neutral temperatures by fitting for each building a linear regression between thermal sensation votes and indoor temperatures and deriving (only for statistically significant regression coefficients) the temperature corresponding to a thermal sensation vote equal to 0. The smaller sample size of the EN 15251 database (a total of 4,655 questionnaires) and the consequent difficulties in obtaining significant regression coefficients made Nicol and Humphreys use the Griffiths method for calculating comfort temperatures for each interviewed occupant. This method consists in calculating for every observation the operative temperature which would have corresponded to a thermal sensation vote equal to 0, assuming that each unit of the seven-points ASHRAE thermal sensation scale corresponds to a 2°C change in the operative temperature.

1.2 Major issues with the adaptive models

The adaptive thermal comfort theory has radically changed the way of undertaking thermal comfort research. By analysing field data collected in real buildings adaptive thermal comfort studies have given the possibility to include psychological and behavioural aspects which were mostly ignored in Fanger's laboratory experiments.

For example, perceived ability of environmental control has been recognized as a fundamental psychological variable affecting the human thermal comfort response (Boerstra and Brager, 2012; Boerstra et al., 2015). This finding has the potential to influence the design of naturally ventilated buildings and motivate the introduction of smart personalized thermal control systems. Also, thanks to the results of thermal comfort field studies, thermal neutrality has been observed to not always coincide with the preferred thermal sensation of the occupants (Humphreys, 1976; De Dear et al., 1998; Schweiker et al., 2017), proving new important insights on how to use and interpret thermal perception scales.

The idea of deriving a thermal comfort model from field data and the claim of modelling not only the human physiological response but also the psychological and behavioural aspects of thermal adaptation, are all very important attributes of the adaptive theory.

However, the interactions between physiological and psychological states and their impact on the thermal response are very complex. Human behaviour adds up to this complexity by mediating the human physiological and psychological response to a changing thermal environment. The adaptive theory responds to this complexity by providing designers and practitioners with extremely simplified linear models (EN 15251 and ASHRAE-55) relating indoor comfort temperatures and outdoor temperatures. This simplicity has been for many year the principal strength of the adaptive models, regarded as easily understandable and applicable models with the potential for promoting a sustainable design. Unfortunately, this has precluded a deep understanding of the physiological, psychological and behavioural mechanisms underlying thermal comfort and has placed the adaptive theory on a lower rank respect to more complex physiological models, such as Fanger's PMV/PPD model (Parsons, 2002).

In particular, the models deriving from the adaptive theory (EN 15251 and ASHRAE-55) provide practitioners with a simplified linear relationship which considers only outdoor temperature as possible predictor of the comfort temperature, hence excluding all the other well-known physiological variables affecting thermal comfort, such as air humidity and air velocity. This simplification is assumed without providing a strong theoretical explanation for the exclusions of the other traditional Fanger's basic thermal comfort parameters (Parsons, 2002; Halawa and Hoof, 2012). This thesis identifies this simplification as one of the main limitations of the existing adaptive models and thus a key problem to be investigated.

A second limitation is related to how the adaptive model is currently used. The work on the European adaptive model suggests that people in warm climate zones prefer warmer indoor temperatures than people living in cold climate zones. However, in reality the model is used in a climate-agnostic manner. For example, the European model predicts that at a mean outdoor air temperature of 25°C, 80% of occupants will find it thermally acceptable until 29°C - whether these are located in Northern England or Southern Italy. It is however not demonstrated that occupants in Northern England will effectively responds to increasing temperatures in the same way as people in Southern Italy. This, and the fact that the underlying data for the model derives primarily from offices, creates difficulties in the application of the model and suggest that more research from longitudinal field studies is needed in order to validate the applicability of the adaptive models in contexts different than those from which they have been derived. This thesis identifies this problem as a second key topic to be investigated.

Finally, a third problem concerns how to define and study adaptive thermal comfort in the future built environment where feedback are expected to be a major aspect of the smart meter roll-out across the world. Real-time and context-aware feedback have the potential to influence the way occupants interact with their buildings and can, ultimately, affect their thermal comfort. However, this impact is still unknown, especially within the framework of adaptive thermal comfort. This thesis identifies this gap as another key problem needing further investigation.

1.3 Research aims and thesis outline

This thesis aims to improve the statistical methods and models currently used in adaptive thermal comfort research by analysing data either collected during newly performed field studies or already available in the literature. This overall aim is achieved by addressing three major gaps which have been identified and described in the previous section. These gaps are here used to generate the following main **R**esearch **Q**uestions:

RQ 1. What is the effect of real-time and context-aware feedback on occupant perceived environmental control, adaptive thermal comfort and behaviour?

RQ 2. Is the European adaptive thermal comfort model effectively able to predict occupant thermal comfort in residential homes in UK?

RQ 3. What is the influence of relative humidity on adaptive thermal comfort? Can new statistical analysis techniques reveal this sought-after relationship?

Each of these **RQs** are addressed in three key chapters (**Chapter 2**, **Chapter 3** and **Chapter 4**), each one based on a first-author journal publication. The content of the thesis is therefore organized around these three central chapters.

An appendix reports the results of three additional studies providing further supporting knowledge on both the theory and the practice of adaptive thermal comfort. The three studies are each based on a journal paper where the author contributed to ideas and analyses.

Chapter 2 and **Chapter 3** report the results of two case studies planned and performed over the course of this PhD. As part of these field works, environmental and air quality data have been collected along with occupant survey data. The analyses done on the collected thermal comfort data have allowed to better understand the statistical methods used in adaptive thermal comfort research. In particular, they have made it possible to critically review the statistical techniques used to model thermal comfort and reflect on the limitations of the methods used to derive occupant neutral temperatures.

These analyses and reflections have then been elaborated and further expanded in **Chapter 4** which chronologically represents one of the last published paper of this thesis but it has indeed been thought and developed over the entire course of this PhD. In this chapter global thermal comfort field data available in the literature are used to demonstrate the inability of the existing methods to correctly predict occupant neutral temperatures and their limitations in correctly model thermal comfort. Hence, new and better methods that considerably advance the science of adaptive thermal comfort are proposed.

The content of the three main Chapters and of the Appendix is organized as follows:

- **Chapter 2** reports results from the first thermal comfort field study carried out during the period of this PhD. This study aimed to observe and quantify the effect of real-time and context-aware feedback on occupant perceived environmental control, their comfort and energy behaviours (**RQ 1**). The study used in-depth energy, environmental and motion sensing to generate real-time feedback through a smartphone application. Subjective data and clothing levels were concurrently collected through questionnaires allowing the long-term monitoring of occupant thermal comfort and of their energy behaviours.

- **Chapter 3** presents data monitored within the second thermal comfort field study carried out over the course of this PhD. The study collected temperature, air quality and thermal comfort survey data over two years in vulnerable and non-vulnerable UK homes. Temperature and air quality data were analysed to assess the presence of overheating and its potential causes. The collected thermal comfort survey data were validated against the European adaptive model to test the applicability of the model in UK residential households (**RQ 2**).
- **Chapter 4** analyses the effect of relative humidity on occupant thermal sensitivity using data collected by reviewing thermal comfort field studies available in the literature. The study also uses the freely accessible ASHRAE RP-884 data to compare the ability of different statistical methods to correctly predict thermal comfort. Using the new knowledge gained by undertaking an innovative analysis, the RP-884 data are cast within a new humidity-adjusted model of adaptive thermal comfort (**RQ 3**). Finally, the use of the new model in building performance assessment is demonstrated across a range of global climates. This study originates from the limitations highlighted in the previous two chapters and further expands on the used methods. Unlike the previous two chapters, Chapter 4 has a global geographical scope and importance and represents the main theoretical contribution of this PhD to the science of adaptive thermal comfort.
- The **Appendix** reports the result of three additional studies. The first represents the first field study on summer and winter thermal comfort in desert refugee camps in Jordan. The collected data provide new insights on the comfort conditions and adaptive potential of refugees living in long-term encampments. The second ideates a new method of assessing probabilistic adaptive thermal comfort for resilient building design based on weather-variability. The third is the first study on the applicability of prevailing thermal comfort standards in the South American country of Colombia.

Chapter 2

The effect of real-time context-aware feedback on occupants' heating behaviour and thermal adaptation

Abstract

Studies have shown that building energy demand in identical dwellings could vary by a factor of three. Differences in occupant behaviour – i.e. purchase, operation and maintenance – have been implicated as a strong source of these differences. The literature suggests that feedback on energy use to building occupants – particularly real-time feedback – can be used to prompt lower operation-related energy behaviours. This is particularly true for thermal demand which, in cold countries, accounts for four times as much energy use as non-thermal demand. However, there is little evidence to support this claim. Further, there are concerns that the actions that allow occupants to lower heating energy use could negatively impact their comfort by lowering indoor temperatures or air quality below acceptable thresholds. We report results from a winter field study that used in-depth energy, environmental and motion sensing to generate real-time context-aware feedback through a smartphone application. Subjective data and clothing levels were concurrently collected through questionnaires. Our results suggest that real-time feedback could lower radiator and room temperatures without significantly affecting occupant thermal comfort. The results also show that real-time feedback could contribute to an increase in occupant perceived environmental control (a key variable in the theory of adaptive thermal comfort) while prompting lower heating energy behaviours.

Preamble

This Chapter reports the results of a field experiment carried out at the University of Bath campus. This experiment represents the first long-term monitoring study of thermal comfort and air quality performed during the period of this PhD. The aim of the study is to detect changes in the adaptive thermal comfort responses of the participants as a result of an energy and environmental feedback intervention. Hence, this Chapter specifically aims to address **R**esearch **Q**uestion **1**.

This research was done as part of the EPSRC-funded ENLITEN (ENergy LIteracy through an intelligent home ENergy advisor) project. The project aimed at reducing building energy use by understanding and influencing changes in the habitual behaviours of occupants. As part of this project, low-cost Arduino-based sensors and an intelligent In-Home Display (IHD) were developed for providing real-time energy and environmental feedback to occupants of social homes in Exeter, UK. The experiment reported in this Chapter represents a pilot study towards the realization of the main intelligent In-Home Display (IHD). The specific focus of this field experiment is on detecting and quantifying changes in occupant energy behaviours and comfort in the framework of adaptive thermal comfort. This experiment has been carried out one year before the main ENLITEN study took place. The ENLITEN monitoring equipment was employed in this experiment, while the mobile application for the feedback was developed by an undergraduate student of Computer Science.

Before the commencement of the data collection, ethical approval was sought and obtained from the research ethics committee of the Department of Architecture and Civil Engineering of the University of Bath. All the participants signed a consent form at the beginning of the study in which they were assured that their data were treated confidentially and that they could withdraw from the research at any stage.

This Chapter is totally based on a same-titled paper published in Energy and Buildings in 2016, more details on the specific contributions from each author are provided in the next Section.

Declaration of Authorship

This declaration concerns the article entitled: The effect of real-time context-aware feedback on occupants' heating behaviour and thermal adaptation	
Status	Published in the Special Issue of Energy and Buildings "Occupancy Behavior in Buildings: Modeling, Simulation and Applications".
Details	**Marika Vellei**, Sukumar Natarajan, Benjamin Biri, Julian Padget & Ian Walker, The effect of real-time context-aware feedback on occupants' heating behaviour and thermal adaptation, Energy and Buildings, 2016, Volume 123, Pages 179-191, ISSN 0378-7788. DOI: doi.org/10.1016/j.enbuild.2016.03.045
Authors' contribution	The author of this thesis has primarily (80%) contributed to defining the methodology adopted for the field experiment and to writing the manuscript. The mobile application has been entirely (100%) developed by B. Biri, but the author of this thesis contributed to the design of the application interface. Sensors installations and processing and statistical analysis of the data have been entirely (100%) carried out by the author of this thesis using the programming language Python. Each author's exact contributions to the article is outlined below: **M. Vellei**: Formulation of ideas (80%), Design of methodology (80%), Collection/Processing/Analysis of data (100%), Preparation of the manuscript (80%). B. Biri: Formulation of ideas (5%), Design of methodology (5%), Development of the smartphone application (100%). S. Natarajan, J. Padget and I. Walker: Formulation of ideas (15%), Design of methodology (15%), Editing drafts of manuscript (20%).
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.
Date and Signature	

2.1 Introduction

The domestic sector accounts for approximately 24% of the world energy consumption (IEA, 2015). In cold climates, 32% of this consumption, on average, is due to space and water heating (IEA, 2015). However, in highly industrialized countries, heating energy use represents a far higher proportion of the domestic energy demand, e.g. 57% in the UK (BEIS, 2013).

Building space heating energy consumption depends on several *physical* factors:

- Geographical factors, i.e. the specific local climate and location (rural, suburban or urban).
- Building characteristics, i.e. the building type, the building thermal properties (which depend on infiltration, insulation, orientation, glazing, etc.) and the floor area.
- Efficiency of the space heating system used (gas central heating, district heating, etc.).

Non-physical factors such as economic and social factors have also a strong role to play but, since they are more difficult to quantify, little is known about the magnitude of their effects which are often neglected when estimates of building performances are made. The energy behaviour of building users represents the expression of these non-physical factors which act as underlying drivers and antecedents of occupant actions. In this study, we define energy behaviours as those conscious or unconscious actions taken by the occupants that result in energy consumption in the building. See Section 2.2 for examples under behavioural adaptation.

Recent research has highlighted the potential impact on heating energy use arising from differences in occupant behaviour (Juodis et al., 2009; Andersen, 2012; Gram-Hanssen, 2010; Urban and Gomez, 2013). For example, occupant characteristics and behaviour have been shown to be responsible for 4.2% of the variation in space and water heating energy consumption in the Dutch residential stock (Santin et al., 2009). Similarly, in the emerging domain of domestic energy literacy research, several studies have examined the impact of increasing literacy on electricity-related behaviours (Kavousian et al., 2013; Delmas and Kaiser, 2014; Emeakaroha et al., 2014; Peschiera et al., 2010). *Energy literacy* in this context may be defined as occupant awareness of the impact of their individual behaviours on building energy use.

However, few studies have investigated the effect of increasing energy literacy on the arguably more important topic of heating energy consumption (Huebner et al., 2013). Further, whilst some studies have begun to focus on the impact of information dissemination on occupant heating energy use (Schweiker and Shukuya, 2011; McMakin et al., 2002), to our knowledge, no studies have investigated the effect of real-time context-aware feedback on occupant heating behaviour, specifically thermal adaptation and comfort. Understanding the links between *feedback*, *behaviour* and *subjective comfort* is important if we are to effectively influence energy-saving behaviours since perceived reductions in comfort are a major impediment to end-users accepting feedback and advice (Buchanan et al., 2015). This paper sets out to address this important gap by investigating the effect of *real-time* and *context-aware* feedback on occupant adaptive actions, thermal comfort and perceived environmental control in the context of their heating energy use.

In a recent critical review on the efficacy of feedback, Buchanan et al. (2015) has outlined the importance of the *human factor* when designing effective feedback strategies. According to Buchanan et al. (2015), feedback must be designed with a user-centred approach in order to "enable users to readily understand the habits and routines that generate their household energy patterns and thus make more concrete the viable energy saving actions available to them". Following the indications of Buchanan, we adopted real-time feedback since many studies in the domain of electricity use have shown that immediacy increases salience and user engagement, and also provides the potential for greater energy savings (Wood and Newborough, 2003; Vine et al., 2013; Allen and Janda, 2006). Furthermore, context-awareness was also considered necessary because, in order to show "available and viable energy saving actions", feedback must respond to the context in which the energy behaviour has occurred (Buchanan et al., 2015).

2.2 The dynamic model of thermal adaptation

The building indoor climate (e.g. air humidity, dry-bulb temperature, radiant temperature, air velocity) and occupant personal physiological factors (e.g. age, gender, health situation, clothing, activity level) affect occupant thermal situation producing different *environmental stimuli* (Figure 2.1). If we imagine two occupants ideally exposed to the same environmental stimuli, their thermal perception is not the same but depends on their subjective *thermal expectations and preferences* (Figure 2.1). In fact, according to the *adaptive model of thermal comfort*, thermal comfort is not merely the result of a body thermal balance but is the outcome of a continuous process of adaptation involving three types of self-regulatory actions: *physiological*, *psychological* and *behavioural* (Brager and Dear, 1998; Nicol and Humphreys, 2002; Dear and Brager, 2001).

Physiological adaptation is any physiological alteration which happens in response to ambient thermal changes (Liu et al., 2012). According to Dear and Brager (2001), for the conditions and the activities typically encountered in residential and office buildings the slow process of physiological acclimatization has only a minimal influence on the thermal experience and, therefore, only psychological and behavioural adaptation affect occupant thermal acceptability.

Psychological adaptation includes any psychological reaction to sensory information (e.g. habituation, relaxation of thermal expectations, gradual change of preferences, etc.) (Schweiker et al., 2012). Many recent studies (Cao et al., 2014; Daniel et al., 2015; Cao et al., 2011; Liu et al., 2014) have tried to identify and quantify the role of *cognitive and psychological factors* in the process of psychological adaptation (Figure 2.1); those factors include:

- perceived environmental control,
- personal beliefs and cultural values,
- past thermal experiences,

- habits,
- perceived rewards and benefits in terms of comfort/health and monetary.

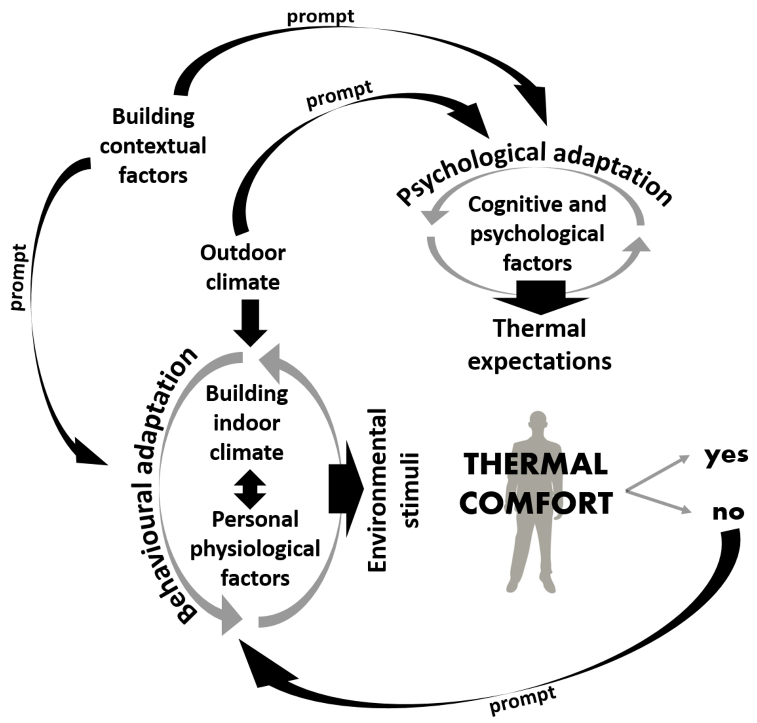


Figure 2.1: The dynamic model of thermal adaptation.

In particular, the literature highlights that occupant *perceived ability of environmental control* is a key psychological variable in defining occupant thermal expectations (Brager and Dear, 1998; Zhou et al., 2014; Haldi and Robinson, 2010; Boerstra et al., 2015; Karjalainen and Koistinen, 2007). High perceived levels of control have been found to positively influence both thermal satisfaction (Zhou et al., 2014; Brager et al., 2004; Karjalainen, 2009) and productivity (O'Neill, 1994). Occupant perceived control depends on *building contextual factors*, i.e. on the availability, accessibility and transparency of means for exerting adaptive opportunities in buildings (e.g. the presence of openable windows). Since people in homes have more possibilities for thermal adaptation and have higher levels of perceived control, they are generally more satisfied with their environment than in their offices (Mishra and Ramgopal, 2013). Several studies have also demonstrated that open plan offices are the environments with the lowest acceptance among their occupants (Mishra and Ramgopal, 2013). This is due to the limited adaptive opportunities available as well as to the low levels of perceived environmental control.

Behavioural adaptation refers to all the conscious or unconscious actions that, when the environmental stimuli are perceived as discomforting, a person can take in order to modify the building indoor environment, their personal situation or both of these (Figure 2.1). This is in agreement with the fundamental precept of the adaptive model: "if a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort" (Nicol and Humphreys, 2002). Of the three forms of adaptive opportunities, this is the one in which occupants have the opportunity to play an active role. Adjustments are both personal and environmental and their availability, ease and effectiveness depends on building contextual factors (Haldi and Robinson, 2010). This is shown in Figure 2.1.

Personal adjustments include:

- putting on/taking off clothing,
- changing activity level (e.g. having a siesta in the hottest moment of the day, taking a walk inside or outside, starting cooking),
- changing posture of the human body (e.g. curling up/cuddling up),
- moving to a different location (e.g. going to bed, visiting a friend),
- taking in hot/cold food or drinks,
- taking a hot bath or a cold shower.

Environmental adjustments include:

- modifying shadings,
- switching on the fan or the air-conditioner,
- turning up the thermostat,
- lighting a fire,
- opening/closing windows or doors,
- drawing curtains,
- indirectly modifying heat gains turning on appliances (e.g. TV, laptop).

Therefore, building contextual factors have an impact on both behavioural and psychological adaptation. The work of O'Brien and Gunay (2014) identifies the following main building contextual factors as external drivers of occupant thermal adaptation in office buildings:

- occupancy period,
- availability of personal control (e.g. is there a window in the room?),
- accessibility of personal control (e.g. is the window close to the occupant? is the window openable? to which degree?),
- complexity and transparency of automation systems,
- presence of mechanical/electrical systems,
- view and connection to outdoors,
- interior design,
- socio-cultural constraints (e.g. dress code in office buildings),
- visibility of energy use.

For the case of residential buildings we need to add economic factors (i.e. the operating costs of heating and cooling). A study conducted in Taiwan observed that air-conditioning was used sporadically in homes where opening of windows was the preferred means for controlling indoor conditions, while in offices air-conditioning was always on (Hwang et al., 2009). This study shows that the operating costs of air-conditioning have an effect on occupant thermal adaptation making them largely use air-conditioning when money is not their concern (i.e. in their office).

Real-time and context-aware feedback reshapes the building contextual factor *visibility of energy use*. In order to be effective, they should be able to affect occupant psychological adaptation (i.e. their thermal expectations and preferences) and prompt *good* energy behaviours (Figure 2.2). Occupant thermal adaptation can lead to high or low energy consumption depending on how the drivers are affected. In this context, we characterize a *good* adaptation as one resulting in a low heating energy use. For example, if the result of an adaptation in winter would be setting the thermostat at 23°C, wearing shorts and t-shirt and opening the window to generate breeze then this adaptation would be considered *bad*.

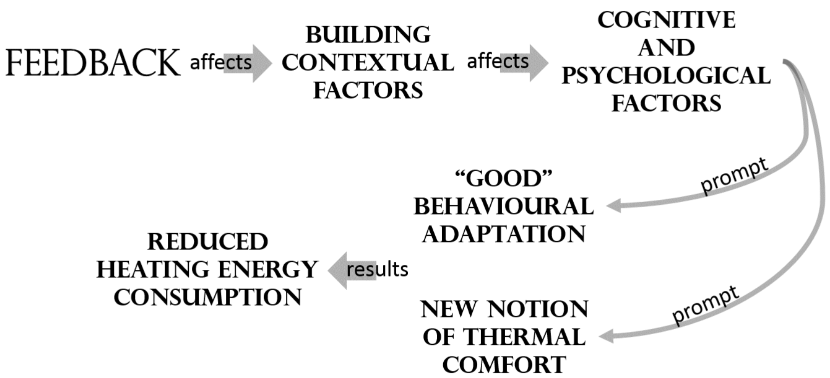


Figure 2.2: The effect of feedback on heating energy use.

The aim of this work is to detect and quantify changes in occupant psychological factors (perceived environmental control), level of *good* behavioural adaptation (clothing and ventilation rates) and thermal comfort (neutral temperatures) as a result of the feedback intervention.

2.3 Methods

2.3.1 Participants

The experiment monitored 15 volunteer subjects occupying near-identical single-occupancy rooms on the university of Bath campus (see Section 2.3.3). The participants signed a consent form at the beginning of the study in which they were assured that their data were treated confidentially. They were all first year undergraduates (18-year-old students) with a male-female gender ratio of 1.14 (male = 8, female = 7). They were of various nationalities, but all were European. At the time of the experiment, all the students had lived in their rooms for about 6 months.

2.3.2 Experimental procedure

The field study had an overall duration of six weeks, divided into two phases of three weeks each. The first phase (*control phase*) consisted of monitoring the student rooms, with no feedback. In the second phase (*experimental phase*), students were provided with feedback via their smartphones, with a specially developed in-house application (Figure 2.5). The experiment started on the 16 February 2015 and ended on the 29 March 2015.

2.3.3 Monitored rooms

The 15 monitored rooms are part of three neighbouring residential blocks, on the University of Bath campus. The three buildings are naturally ventilated and are identical in terms of exposure and building characteristics. In each of the three buildings the source of heating is a natural gas boiler. The heating schedule was regulated by the estate manager but remained the same during the 6 weeks for the 3 buildings. Dimensions and type of furniture in the rooms are all nearly identical. Each room has a floor area of about 8 m^2 and contains a water borne radiator with a thermostatic valve. Students were therefore allowed to adjust their valve and also to set the valve to zero.

2.3.4 Physical measurements

Each room was equipped with environmental and motion sensors reporting every minute to a university-hosted database, allowing in-depth real-time monitoring of the rooms. The sensors consisted of a dry-bulb temperature sensor, a relative humidity sensor, a CO_2 sensor, a temperature sensor fitted on the radiator and a PIR infrared motion sensor to detect room activity (Table 2.1). Environmental sensors were placed at a height approximately of 1 m from the floor. They were placed where they could not be hit by direct solar radiation, at least one meter away from the radiators and not less than half a meter away from any external wall (Figure 2.3).

We did not continuously measure radiant temperatures and air velocities. The reduced dimensions of the room did not allow us to place two additional sensors to the three already employed. However, an in-depth inspection of the rooms during the sensor installation visits allowed us to exclude the presence of human-noticeable high air velocity and radiant asymmetries. So, we could disregard these two parameters for the analysis of comfort conditions.

Outdoor atmospheric conditions were recorded at a weather station located on the roof of a building, approximately 200 m from the student dormitories.

Table 2.1: Instrumentation details.

Parameter	Range	Accuracy
DS18B20 temperature sensor (used for both air and radiator surface temperature measurements)	-10 to 85°C	± 0.5°C
RHT03 humidity sensor	0 to 100%	± 2%
K30 Senseair CO_2 sensor	0 to 5000 ppm	± 30 ppm
HC-SR501 PIR Infrared Motion Sensor	120°, 0 to 7 m	n.a.

2.3.5 Psychological measurements

Students were asked to fill two thermal comfort questionnaires per day after being in their room for at least 30 minutes. In the first three weeks the questionnaire was in a paper format and each student indicated the exact date and time when the questionnaire was taken. In the last three weeks the questionnaire was given through the smartphone application and, therefore, the date and time were automatically recorded. This enabled the collection of 624 valid questionnaires. Each participant provided between 14 and 66 questionnaires, for an average of 42 questionnaires per student.

The daily questionnaire was adapted from ASHRAE (2013) and ISO (2005) standards and included the information reported in Table 2.2.

At the end of the first and second experimental phases, students were asked to fill an additional questionnaire designed to measure overall satisfaction with the room and perceived environmental control (Table 2.3). The aim was to detect changes to these responses as a result of the feedback.

Students' satisfactions levels before and after the feedback are reported in Tables 2.4, 2.5 and 2.6, for each student. Students' levels of overall perceived control (mean values of temperature and air quality perceived control) before and after the start of the feedback are reported in Table 2.8.

Figure 2.3: View of the residential blocks (left) and of a typical student room (right) showing the positioning of the sensors.

2.3.6 The application

The smartphone application developed for this study is shown in Figure 2.5. It was developed using the Ionic framework allowing the software development to be deployed on both Android and iOS platforms (since there was a 50:50 split between these operating systems within the recruited occupant sample).

There are a number of ways to design feedback interfaces. In previous works we have shown that the design of the feedback system could have a significant impact on how well a feedback system performs, although the simple act of providing feedback itself has an effect on occupant behaviour (Chiang et al., 2012, 2014). Since the optimal design of an interface is not the focus of the present work, we followed the main indications given by Lohr (2000) which suggest:

- to keep clear the background and foreground distinctions in order to make the display visible,
- to organize the interface elements into easily distinguishable and comprehensible

sections.

Table 2.2: Daily questionnaire.

Current clothing	Clothing items and corresponding insulation values were adopted from both ASHRAE (2013) and ISO (2005) standards.
Activity level in the previous 30 minutes	3 possible levels of activity could be chosen (Hong et al., 2009).
Thermal sensation vote (TSV)	How are you feeling right now? Measured on the ASHRAE seven-point Likert scale.
Thermal preference vote (TPV)	If you could change the current temperature in your room, what would you prefer it to be? Reported on Nicol's scale: –1 (much cooler), –0.5 (a bit cooler), 0 (no change), 0.5 (a bit warmer), 1 (much warmer).
Thermal acceptability vote (TAV)	What do you think about the temperature of your room right now? Reported in the scale: 1 (clearly acceptable), 2 (just acceptable), 3 (just unacceptable), 4 (clearly unacceptable).
Perceived air quality	How do you perceive the air quality right now? Reported in the scale: 1 (clearly acceptable), 2 (just acceptable), 3 (just unacceptable), 4 (clearly unacceptable).

Table 2.3: Additional questionnaire.

Satisfaction with the thermal environment	In general how do you find the overall thermal environment in your room? 1 (very dissatisfying), 2 (slightly dissatisfying), 3 (acceptable), 4 (rather satisfying), 5 (very satisfying).
Overall humidity sensation	In general how do you find the overall humidity sensation in your room? 1 (very dry), 2 (slightly dry), 3 (neutral), 4 (slightly humid), 5 (very humid).
Overall perceived air quality	In general how do you find the overall air quality in your room? 1 (very dissatisfying), 2 (slightly dissatisfying), 3 (acceptable), 4 (rather satisfying), 5 (very satisfying).
Perceived control of temperature	How well do you feel you can personally control the temperature in your room? 1 (no control), 2 (light control), 3 (medium control), 4 (high control), 5 (total control).
Perceived control of air quality	How well do you feel you can personally control the air quality in your room? 1 (no control), 2 (light control), 3 (medium control), 4 (high control), 5 (total control).

Air temperature is a key parameter for both thermal comfort and heating energy consumption and, therefore, is the content of the first two sections of the application (respectively current and mean daily temperature information). Furthermore, since social comparison can be a strong motivating factor especially in a student environment (Emeakaroha et al., 2014), a comparative element (mean daily room temperature of the other students in the residential block) was introduced to further promote behavioural changes. In the third section of the application, we provided students with a bar chart of today building heating energy cost compared to the previous day (*yesterday*). Finally, since historical feedback has been found to be easily understandable and useful for users (Vine et al., 2013), in the fourth section we introduced a seven-day overview of daily building heating energy costs.

The application uses real-time data and a set of heuristic rules to produce the following energy savings tips:

- If Friday: The weekend is coming! Remember to turn off the radiator (by adjusting the valve to zero) if you don't plan to be in your room.
- If between 8 PM and 10 PM: Do you feel cold when you go to sleep? Rather than turning up the radiator have you tried wearing a heavy pyjama or using extra blankets? Drawing your curtains can also help to keep the heat in!
- If $CO_2 < 600$ ppm: Oops! You might have opened both your window and door, which means that if the radiator is on, you are heating the outside air! If you opened these because your room was feeling stuffy, then remember to close them back quickly to save energy.
- If $CO_2 > 1800$ ppm: Your room is getting stuffy! Open your window for a while and get some fresh air! Remember to close it back though as otherwise you are just heating the outside air!
- If room temperature > 21°C: Your room temperature is more than 21°C at the moment. Most people find this quite warm. Turning down your radiator would help save energy. If you still feel cold, have you tried wearing warmer clothes instead?

The heuristic feedback was only based on real-time measurements of room temperature and room CO_2 concentration; it was not possible to use the measurement from the PIR sensors since some students accidentally covered them up.

2.3.7 Monetary rewards

In a domestic setting, the reduction of energy consumption directly impacts fuel bills and can be a powerful motivating factor for undertaking energy saving measures. However,

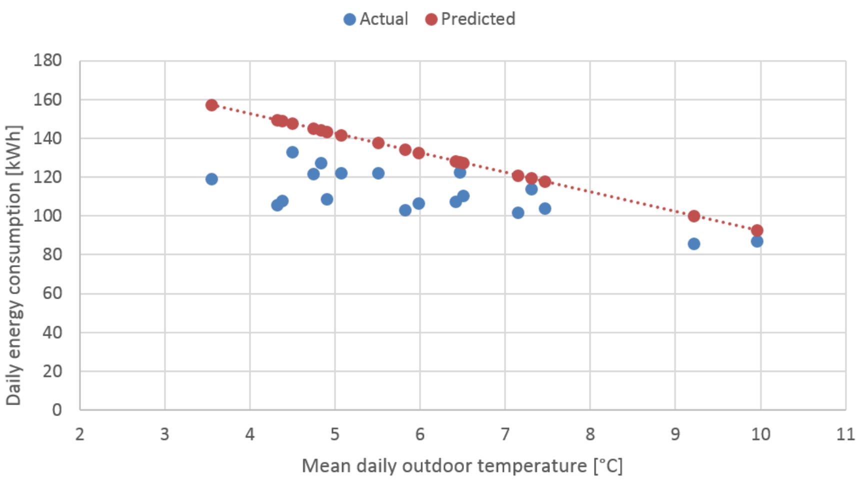


Figure 2.4: Actual and predicted daily energy consumption at different mean daily outdoor temperatures for one of the three monitored residential block.

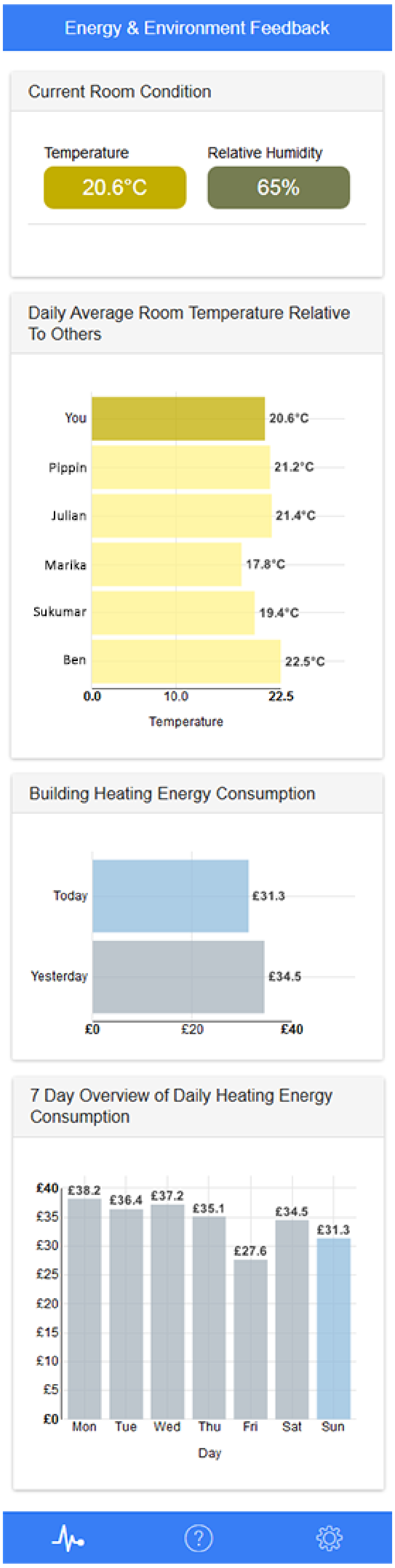


Figure 2.5: Screen of the application.

in a university setting, students do not normally pay for their actual consumption directly since fuel bills are often bundled into the accommodation cost. To simulate as closely as possible the domestic setting in our study, students were rewarded for their energy saving with an amount of money proportional to the energy saved.

Using the energy measurements of the previous 4 months (from 1 October 2014 to 31 January 2015) the daily energy consumption of each residential block was weather-corrected using a linear regression model (red line in Figure 2.4). Energy savings were therefore calculated as the difference between the daily predicted (red dots in Figure 2.4) and actual (blue dots in Figure 2.4) energy consumption.

An artificial gas tariff (of 0.2 £/kWh instead of the 0.03 £/kWh typically paid by domestic consumers) was used for the monetary rewards to make the cost-feedback more salient due to the short duration of the feedback phase. This tariff is the same as the one used for calculating the daily energy costs shown in the application (Figure 2.5). The tariff value was obtained from an estimation of plausible expected energy savings in a study of this duration that would result in meaningful payouts to the participants. This was based on an approach already established in previous works, see e.g. (Chiang et al., 2014). In real homes, the opportunity to contextualise savings against an entire heating season would be available, allowing the numbers to be more meaningful by using real tariffs. Real tariffs can be complicated, for example, most tariffs would also include a standing charge, which is hard to capture in a study of this kind. However, we recognize that tariffs could play an important role in designing feedback strategies and that, in particular, variable rate energy tariffs are expected to become more important in the future. Therefore, further work will be needed to understand if and how variable tariffs can affect behavioural changes.

Students were only rewarded at the end of the experimental phase (i.e. at the end of the six weeks). They earned an average of 7 pounds each during the three weeks (min = 3.5 £, max = 10.2 £).

2.4 Results and discussion

2.4.1 Analysis of the comfort conditions

The heating energy behaviour of building occupants is directly linked to its *primary product*: occupant thermal comfort. Therefore, an analysis of adaptive thermal comfort is the main focus of this work. In this section we describe the overall comfort conditions in the 15 monitored rooms and we introduce the variables used for analysing the effects of feedback on occupant subjective comfort conditions.

The distribution of Thermal Sensation Votes (TSVs) and Thermal Preference Votes (TPVs) is shown in Figure 2.6 (top). Occupants report *no change* thermal preference for *warm*, *slightly warm*, *neutral*, *slightly cool* and *cool* thermal sensation votes. In particular, it can be noticed that there is a prevalence of *no change* votes on the warm side of the thermal sensation. This shows that thermal neutrality does not always correspond to the preferred thermal sensation and that people prefer warm thermal sensations when is cold outside

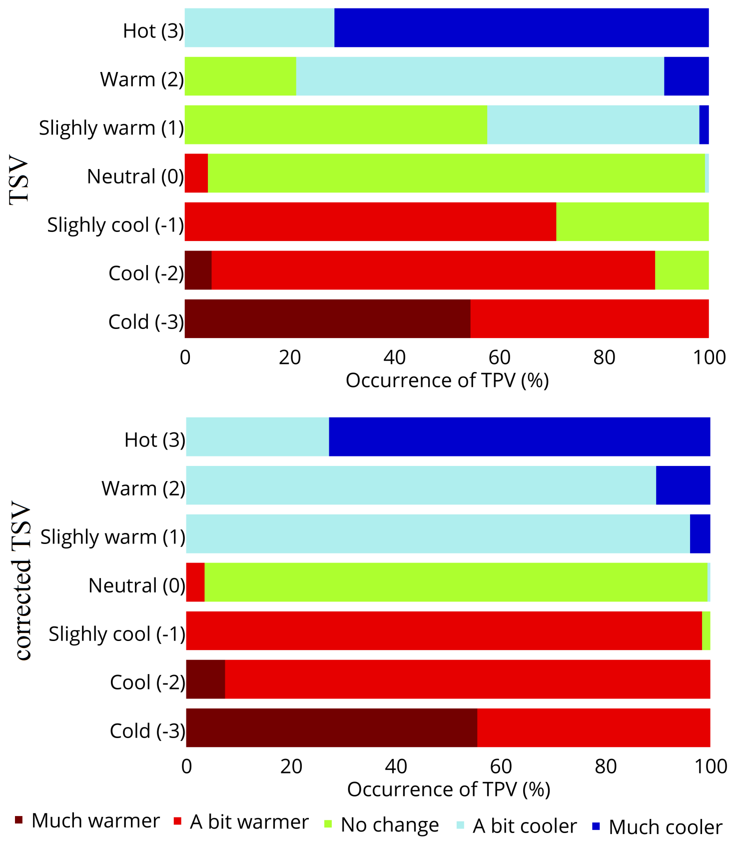


Figure 2.6: The two graphs show the distribution of TPVs (Thermal Preference Votes) expressed as % for different uncorrected (top) and corrected (bottom) TSVs (Thermal Sensation Votes).

(i.e. in winter). This fact is known as the *semantic artefact hypothesis* (Brager and Dear, 1998). If an occupant is *slightly warm* and does not want to change his thermal environment then his/her *slightly warm* sensation, at this moment, implies comfort. The same reasoning applies for *warm*, *cool* and *slightly cool* thermal sensations.

In order to take into account this fact and in order to make more robust the thermal comfort analysis of the next section, non-neutral *no change* votes are re-defined as neutral for the cases when an *acceptable* thermal vote is also expressed. Doing so, a new distribution for the corrected TSVs and TPVs is obtained in Figure 2.6 (bottom). In this new distribution 99% of the non-neutral *no change* votes have migrated from the warm and cool side of the thermal sensations to the central neutral category; this is due to the fact that 99% of the non-neutral *no change* votes are also *acceptable* thermal votes.

In order to further demonstrate the validity of the post-survey elaboration of the thermal votes, TSVs and corrected TSVs are shown together with Thermal Acceptability Votes (TAVs) in Figure 2.7. For the corrected TSVs there is a reduction of *clearly acceptable* votes on both warm and cool side of the thermal sensations; this means that *clearly acceptable* votes migrate from the warm and cool thermal sensation sides to the central neutral category.

According to the ISO 80% acceptability criterion, a thermal environment is regarded as comfortable when 80% of the occupants are feeling between *slightly cool* and *slightly warm* (ISO, 2005). According to this criterion and considering the corrected TSVs, students

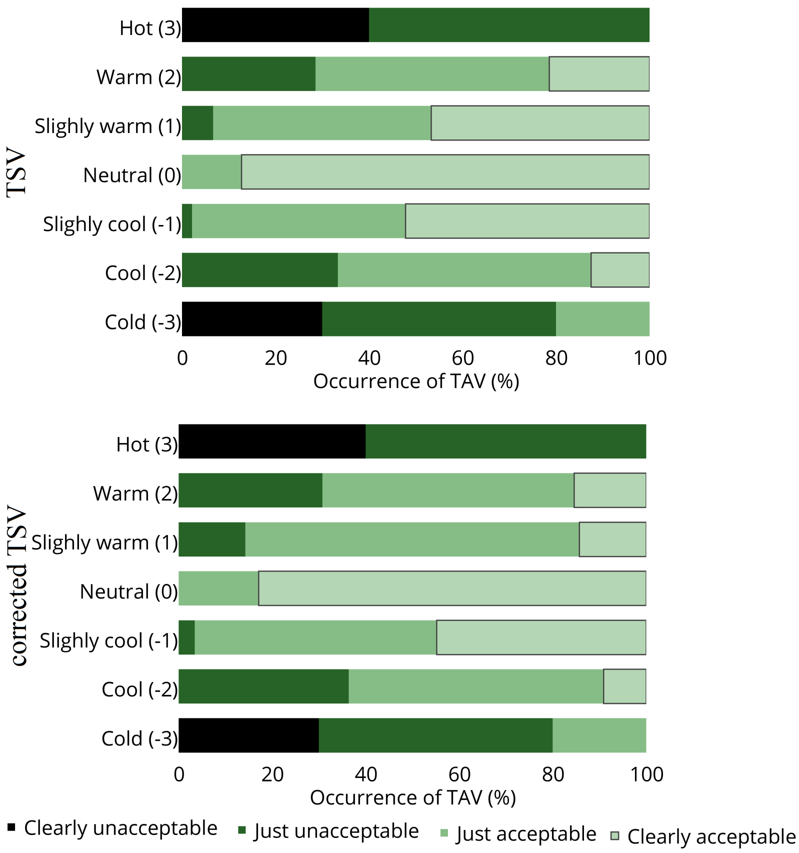


Figure 2.7: The two graphs show the distribution of TAVs (Thermal Acceptability Votes) expressed as % for different uncorrected (top) and corrected (bottom) TSVs (Thermal Sensation Votes).

were comfortable 87% of the occasions. This demonstrate that the rooms can be regarded as thermally comfortable. When considering only the neutral votes (corrected $TSV = 0$), students were comfortable 69% of the times. The percentage of neutral votes for each student varied from a minimum of 36% to a maximum of 91%. This shows that the level of thermal acceptance varied largely among the different students.

2.4.2 The effects of feedback on physical variables

The PIR sensor did not work in all the rooms since some students accidentally covered it. Therefore, occupancy profiles were defined based on the indoor CO_2 concentration and then, in order to check the accuracy of the estimation, inferred occupancy profiles were compared with the PIR data for rooms where measurements were available (Figure 2.8). When comparing the PIR data with the CO_2 profiles, it was evident that if students left the room, CO_2 concentrations decreased due to air movement through the window and the door. Therefore, following a similar approach of Ansanay-Alex (2013), we considered the room unoccupied when the moving average of CO_2 was decreasing or was lower than 500 ppm. This approach excluded those timestamps when the room was occupied but the window or the door was kept opened, but it was able to model occupancy in all the other cases. It is noteworthy that the feedback statements (Section 2.3.6) do not require knowledge of occupancy. Since occupancy was only needed to filter the data we did not require a very accurate estimation of it. The mean and one standard deviation for environmental and CO_2 data filtered based on occupancy are reported in Tables 2.4, 2.5 and 2.6, for each student.

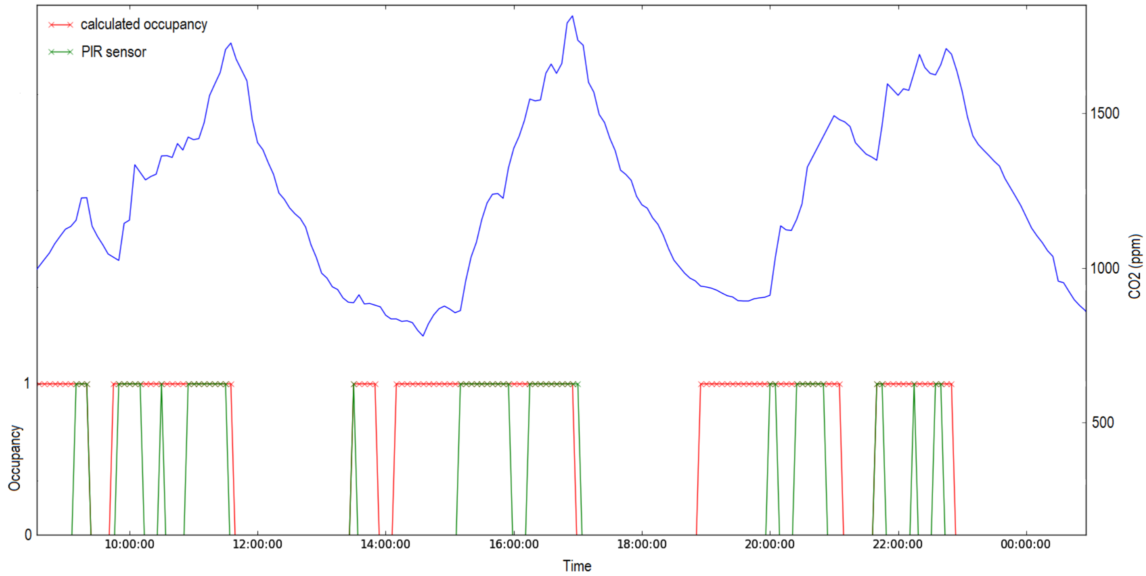


Figure 2.8: Calculated occupancy profiles based on CO_2 concentration.

For the analysis, students were sorted into two groups according to the number of questionnaire they filled in during the feedback period. During this period, the questionnaire was integrated in the application and, therefore, a low number of questionnaires can be associated with a low interaction with the application. However, it is not possible to confirm this since we did not explicitly measure the number of viewings of the application. Group 1 includes students that, during the feedback period, filled in more than 13 questionnaires (an average of 20 questionnaires each during the experimental phase). While students of Group 2, in the same period, filled fewer than 8 questionnaires each (an average of 7 questionnaires each, i.e. 1 every 3 days which is very low compared to the original requirement of 2 questionnaires per day). Finally, one student (Group 3) whose room was monitored for the 6 weeks but who did not receive any feedback since his smartphone was not compatible with the developed application.

The average outdoor temperature during the first three weeks was 5.8°C. During the last three weeks it slightly increased to 6.2°C. Since the heating schedule remained the same, room air temperatures were expected to increase. Room temperature slightly increased for student no. 15 of Group 3 who was monitored for the six weeks but did not receive any feedback; while, for all the students of Group 1 (with the exception of students no. 1 and 2) room air temperatures decreased (Table 2.6). For students no. 1 and 2 (Group 1a) the temperature increase was due to the stricter control of window opening (their mean room CO_2 concentration increased respectively by 25% and 26%). This fact is confirmed by the decrease of radiator temperatures for both students during the last three weeks. Therefore, unlike Group 2, all the students of Group 1 tried to save energy by lowering their radiator settings (Figure 2.9). However, they responded to the lower radiator temperatures through different adaptive responses (Figure 2.10):

- through a stricter control of window opening (Group 1a),
- by wearing more clothing (Group 1b).

For student of Group 1a there is an average increase of CO_2 concentration equal to 18% (Table 2.4) with no noticeable increase in clothing level. While, for students of Group 1a there is an increase of their clothing, on average, of 20% (Table 2.6).

An in-depth analysis of CO_2 room concentrations for Group 1a shows that, while student no. 1 and 4 followed the feedback recommendations to keep CO_2 levels under 1,800 ppm, students no. 2 and 3 exceeded the level of 1,800 ppm for respectively 30% and 20% of the time. This unwanted effect was due probably to the fact that feedback tips were either not seen or ignored. This shows that there is a risk of air quality degradation when trying to save heating energy. This risk needs to be taken into account when designing feedback strategies. At this regard, it is important to notice that the limit of 1,800 ppm is higher than the commonly-referenced value of 1,000 ppm (ASTM, 2012). However, the adopted value of 1,800 ppm (corresponding to a percentage of dissatisfied people equal to 40% (ASTM, 2012)) was intended as a critical limit to not be overcome, 1,000 ppm still being the optimal limit.

In Table 2.3, it can been seen that the average CO_2 concentrations before the feedback are generally higher than 1,000 ppm, this can be attributed to different fact:

- the low ventilation rates in winter,
- the small dimensions of the room,
- the vicinity of the CO_2 sensor to the occupant since it was not always possible to guarantee a distance of 2 m due to the small dimensions of the room.

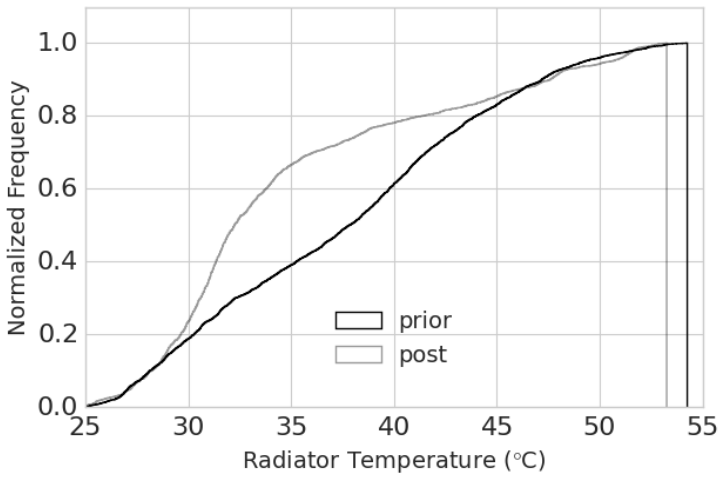


Figure 2.9: Radiator temperatures before (prior) and after (post) the start of the feedback (Group 1).

From the analysis of the clothing levels (Table 2.5 and Figure 2.10) it can be noticed that Group 2 tended to wear less clothing during the feedback phase. Therefore, they responded to the higher indoor temperatures through decreasing their clothing insulation. This fact confirms the previously hypothesized low interaction with the application.

The average outdoor relative humidity was the same during the first and second experimental phase (83%). The indoor relative humidity was in the recommended range 40 - 60% (EN, 2007). Humidity was perceived as neutral by the majority of the students, but 4 out of 14 students perceived it as slightly humid (Table 2.5).

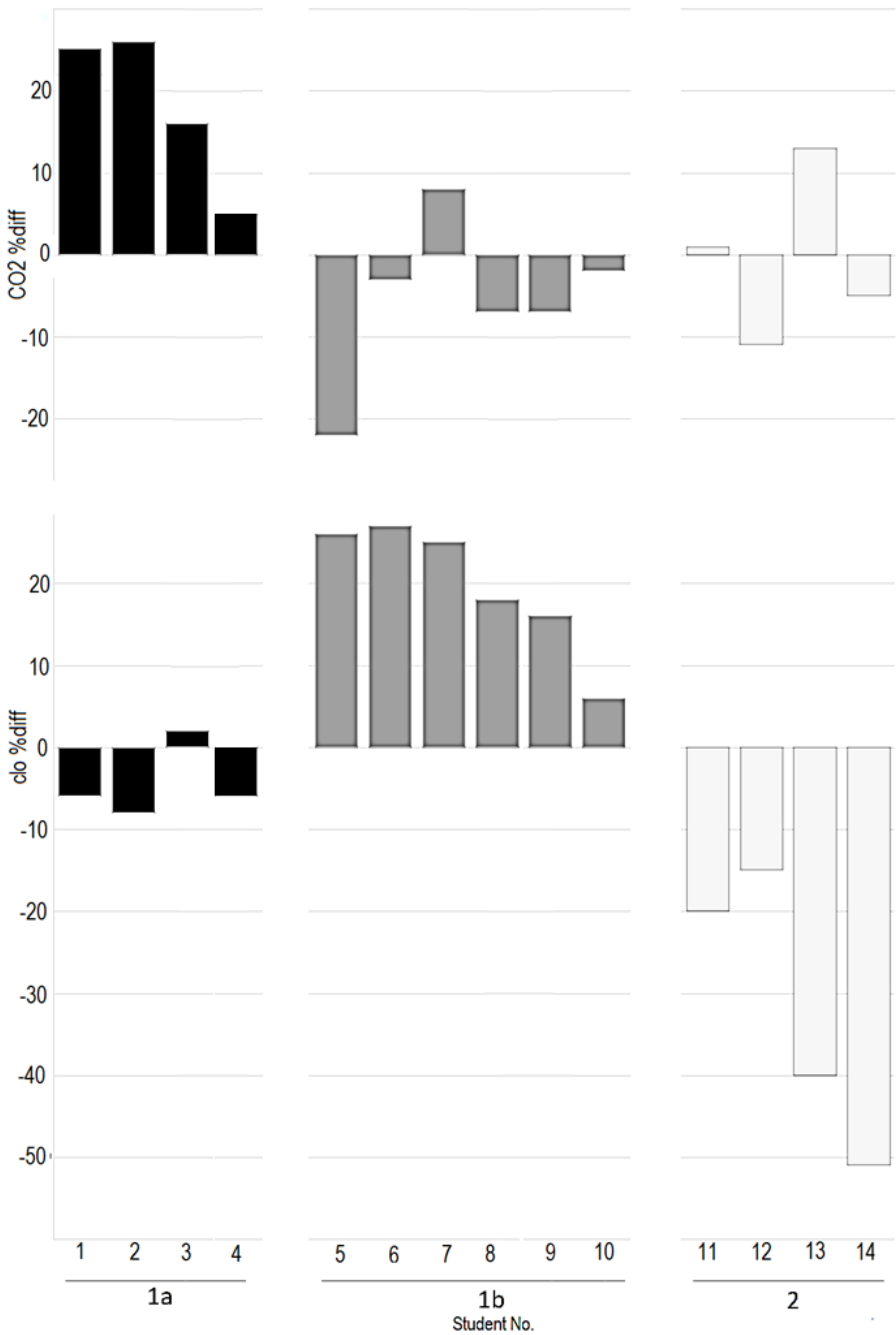


Figure 2.10: Percentage differences in CO_2 concentration (CO_2%diff) and student levels of clothing (clo%diff) before and after the start of the feedback.

2.4.3 The effects of feedback on psychological variables

Due to the limited number of surveyed thermal sensation votes, the analysis of the neutral temperatures for each student before and after the start of the feedback was the most difficult task of this study. In fact, as outlined by Nicol and Humphreys (2010), the two traditional methods of calculating the neutral temperature (i.e. regression and probit analysis) require a large number of responses to give reliable results.

The regression method consists in calculating the mean TSV for each 1°C (or 0.5°C) temperature interval and drawing the regression line, the neutral temperature is the one corresponding to $TSV = 0$ (Cao et al., 2014; Wang et al., 2011). This method assumes that TSV is linearly dependent from the temperature and that no adaptation takes place. In field studies in homes TSV is never only dependent on air temperature. Since people tend to continually adapt and to have more control over their environment, there are many other factors such as clothing, metabolism, behaviours that affect TSV. TSV and room air temperature tend to interact with each other and are, therefore, not necessarily linearly dependent. This has been previously observed in field studies of Oseland (1994), Nicol and Roaf (1996), Nicol and Humphreys (2010), Rijal et al. (2010), and Indraganti (2010b, 2011). Furthermore, this approach is not really rigorous since thermal sensation votes are ordinal variables and, therefore, it is not appropriate to calculate their mean (Haldi and Robinson, 2010).

In this study the regression method did not give robust correlations (e.g. students no. 7-8-9-11 in Table 2.7) and, therefore, it failed to give reliable values. In fact, for many students the majority of the votes were neutral and, so, the method was not able to predict neutral temperatures.

In order to overcome these problems, Nicol and Humphreys (2010) have calculated the neutral temperature using the Griffiths method with the following equation:

$$T_n = T_m - TSV_m/G \tag{2.1}$$

TSV_m is the mean Thermal Sensation Vote, T_m is the mean indoor temperature in °C and G is the assumed regression gradient, also called Griffiths coefficient in /°C.

We used the regression coefficient 0.25 which is usually obtained in field studies according to Nicol and Humphreys (2010) and we calculated the neutral temperature for each student before and after the start of the feedback by computing the mean of the TSVs (Table 2.7). However, this approach suffers the same limitations of the regression method since it implies that no adaptation takes place and it is based on the calculation of the mean of an ordinal variable. Therefore, we propose a new approach for computing the neutral temperatures and we compare the resulting temperatures with the ones obtained with the two methods described above (regression method and Griffiths method, see Table 2.7).

The new method uses the corrected TSVs and is explained by the following algorithm:

$$\text{IF } TSV_{comf} > 80\% \text{ THEN } T_n = \mu(T_0) \tag{2.2}$$

$$\text{IF } TSV_{comf} < 80\% \text{ THEN } T_n = \mu(T_{CH}) \quad (2.3)$$

where T_n is the neutral temperature, TSV_{comf} is the percentage of comfortable votes (i.e. corrected TSVs between -1 and 1), $\mu(T_0)$ is the mean of the temperatures for corrected $TSV = 0$, T_{cold} are the temperatures for corrected TSV lower than -1, C is the percentage of corrected TSVs lower than -1, T_{hot} are the temperatures for corrected TSV higher than 1, H is the percentage of corrected TSV higher than 1, $\mu(T_{CH})$ is the mean of the temperatures comprised between the Cth percentile of T_{cold} and the Hth percentile of T_{cold} (green lines in Figure 2.11).

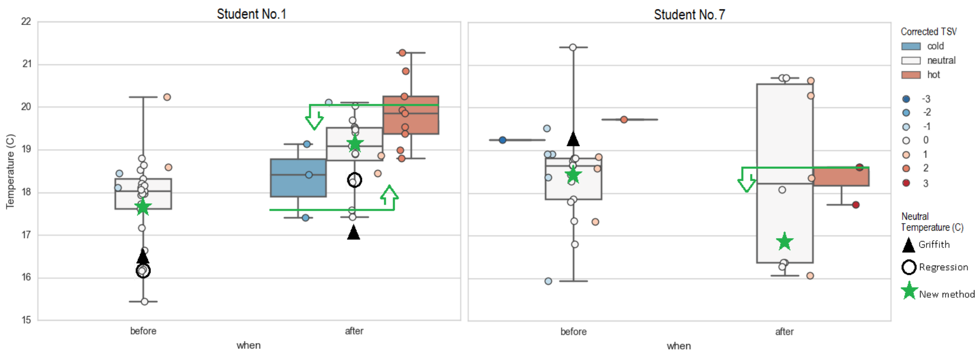


Figure 2.11: Boxplot of neutral, hot and cold temperatures before and after the start of the feedback for students no. 1 and 7. The line within each box is the median, the edges of the box are the 25th and 75th percentiles (indicated respectively as q1 and q3), the thin lines (whiskers) extend to those values between q3 - 1.5*(q3–q1) and q1 + 1.5*(q3–q1).

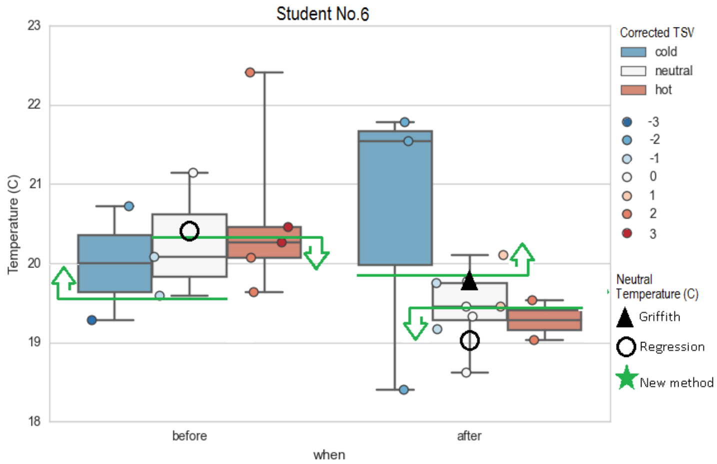


Figure 2.12: Boxplot of neutral, hot and cold temperatures before and after the start of the feedback for students no. 6. The line within each box is the median, the edges of thebox are the 25th and 75th percentiles (indicated respectively as q1 and q3), the thin lines (whiskers) extend to those values between q3–1.5*(q3–q1) and q1 + 1.5*(q3–q1).

In the case of student no. 6 there are not temperatures T_0 between the two percentile of T_{cold} and T_{hot} and, therefore, it is not possible to calculate neutral temperatures with this method (Figure 2.12).

The analysis of the neutral temperatures (Table 2.7) shows that feedback has potential to directly affect the notion of comfort of occupants by changing their neutral temperatures.

Table 2.4: Mean ± one standard deviation of CO_2 concentration and perceived air quality before (prior) and after (post) the start of the feedback.

		CO_2 concentration (ppm)			Perceived air quality	
	No.	prior	post	%diff	prior	post
1a	1	1,023±251	1,278±496	+25%	Acc.	Acc.
	2	1,243±625	1,564±634	+26%	Very sat.	Very sat.
	3	1,064±452	1,233±664	+16%	Acc.	Very sat.
	4	954±220	1,006±231	+5%	Acc.	Acc.
1b	5	1,314±326	1,021±297	-22%	Acc.	Rather sat.
	6	1,272±393	1,239±312	-3%	Slightly dis.	Acc.
	7	1,118±439	1,207±541	+8%	Acc.	Acc.
	8	1,032±271	955±214	-7%	Slightly dis.	Rather sat.
	9	1,194±396	1,108±333	-7%	Acc.	Very sat.
	10	1,016±248	997±261	-2%	Rather sat.	Acc.
2	11	1,334±423	1,342±409	+1%	Rather sat.	Acc.
	12	1,080±326	961±318	-11%	Acc.	Acc.
	13	1,380±620	1,564±698	+13%	Acc.	Acc.
	14	1,131±496	1,072±433	-5%	Acc.	Acc.
3	15	1,048±390	1,085±340	+3%	n.a.	n.a.

Acc.=Acceptable, Sat.= Satisfying, Dis = Dissatisfying, n.a.=not available.

We achieved a reduction of neutral temperature equal to 1.7°C for student no. 7 (Figure 2.11). This also demonstrates that thermal comfort is a *highly negotiable* socio-cultural construct (Liu et al., 2014) and that real-time feedback can prompt occupants adaptive behaviour and reshape their notion of comfort. This process of re-defining occupants notion of comfort can contribute to lower building heating and cooling energy consumption. Of course, this result can only be achieved if there is a sufficient motivation to interact with the application.

Two other important facts can be observed for students of Group 1: (i) overall perceived environmental control increases and (ii) thermal and air quality satisfaction levels increase. The Wilcoxon signed rank test is used in order to analyse differences between the samples before and after the start of the feedback. A non-parametric test is chosen due to the limited sample size and due to the fact that the sampling distribution is non-normal. The selected significance level is $p = 0.05$. For Group 1, perceived control levels for temperature and air

Table 2.5: Mean ± one standard deviation of relative humidity and humidity sensation before (prior) and after (post) the start of the feedback; n.a.: not available.

		Relative humidity (%)		Humidity sensation	
	No.	prior	post	prior	post
1a	1	47±5	50±5	Neutral	Neutral
	2	49±6	55±5	Neutral	Neutral
	3	43±4	44±5	Slightly humid	Slightly humid
	4	44±5	46±4	Neutral	Neutral
1b	5	43±4	42±5	Slightly humid	Slightly humid
	6	48±6	48±5	Slightly dry	Neutral
	7	51±6	51±5	Neutral	Neutral
	8	49±7	50±6	Slightly humid	Slightly humid
	9	48±5	49±4	Neutral	Neutral
	10	48±5	46±4	Neutral	Neutral
2	11	53±7	54±6	Slightly dry	Neutral
	12	48±3	45±3	Neutral	Neutral
	13	50±6	52±9	Neutral	Neutral
	14	45±6	44±5	Neutral	Neutral
3	15	51±5	49±5	n.a.	n.a.

quality are significantly higher (respectively, $W = 8$, $p = 0.046$ and $W = 0$, $p = 0.005$) after the start of the feedback (Median = 3) than before (Median = 2.5). Thermal satisfaction levels are significantly higher after the start of feedback (Median = 4) than before (Median = 3), $W = 0$, $p = 0.0049$. Satisfaction levels for air quality are also significantly higher after the feedback (Median = 3.5) than before (Median = 3), $W = 7$, $p = 0.036$.

2.5 Limitations

Proving the efficacy of feedback in changing occupant behaviours is not an easy task. Therefore, in common with many other studies in this field, we discuss the following limitations of our work:

- *Fallback effect*: This is the phenomenon where *newness* motivates people to change but

Table 2.6: Mean ± one standard deviation of room air temperature, thermal sensation and mean clothing level before (prior) and after (post) the start of the feedback.

		Air temperature (°C)			Thermal satisfaction		Clothing (clo)		
	No.	prior	post	diff	prior	post	prior	post	%diff
1a	1	17.5±1.2	18.8±1	+1.3	Acc.	Rather sat.	0.67	0.63	-6%
	2	21±1	21.1±1	+0.1	Rather sat.	Rather sat.	0.74	0.68	-8%
	3	20.2±1.1	19.9±1.4	-0.3	Rather sat.	Very sat.	0.59	0.6	+2%
	4	19.7±0.6	19.1±0.8	-0.6	Acc.	Acc.	0.7	0.66	-6%
1b	5	21.2±0.7	20.2±1.1	-1	Acc.	Rather sat.	0.73	0.92	+26%
	6	20.2±0.7	19.3±0.8	-0.9	Rather sat.	Rather sat.	0.6	0.76	+27%
	7	18.4±1.2	17.7±2	-0.7	Acc.	Acc.	0.36	0.45	+25%
	8	18.3±1.3	17.6±1.9	-0.7	Slightly dis.	Rather sat.	0.51	0.6	+18%
	9	20.1±1.1	20±1.2	-0.1	Acc.	Very sat.	0.62	0.72	+16%
	10	19±0.6	18.9±0.5	-0.1	Rather sat.	Rather sat.	0.64	0.68	+6%
2	11	20.3±0.8	20.2±1.1	-0.1	Rather sat.	Rather sat.	0.49	0.39	-20%
	12	19.9±0.3	18.9±0.9	-1	Rather sat.	Acc.	0.52	0.44	-15%
	13	21.6±0.9	22.2±0.9	+0.6	Rather sat.	Rather sat.	0.94	0.57	-40%
	14	19±1.1	19.7±1.2	+0.7	Rather sat.	Acc.	0.39	0.19	-51%
3	15	18.5±0.6	18.8±0.7	+0.3	n.a.	n.a.	n.a.	n.a.	n.a.

Acc.=Acceptable, Sat.= Satisfying, Dis = Dissatisfying, n.a.=not available.

this motivation vanishes with time (Wilhite and Ling, 1995). We monitored the effect of feedback for only 3 weeks and conclusions cannot therefore be drawn about their long-lasting effect.

- *Sample size*: The reduced sample size is another limiting factor of this study. Since this work was designed as a precursor to a more in-depth study involving more real homes over a longer period of time, it may be seen as *proof-of-concept* that real-time

Table 2.7: Neutral temperatures calculated with three different methods (Griffith, Regression, New) before (prior) and after (post) the start of the feedback; n.a.: not available.

		Griffith method		Regression method				New method		
	No.	prior	post	prior	R^2	post	R^2	prior	post	diff
1a	1	16.5	17.1	16.3	0.84	18.4	0.82	17.6	19.2	+1.6
	2	21.7	21.8	22.0	0.46	16.5	0.05	21.2	21.3	+0.1
	3	21.1	22.1	20.5	0.76	20.6	0.23	20.8	21.3	+0.5
	4	21.1	20.6	20.2	0.48	21.8	0.37	17.6	19.2	-0.4
1b	5	23.1	23.6	22.7	0.42	21.5	0.63	21.5	21	-0.5
	6	17.5	19.7	20.4	0.35	19.1	0.08	n.a.	n.a.	n.a.
	7	19.4	14.5	15.0	0.05	41.4	0.00	18.5	16.8	-1.7
	8	20.9	22.7	13.8	0.07	5.7	0.09	18.1	19.7	+1.6
	9	20.5	20.2	19.6	0.02	20.1	0.53	20.4	20.1	-0.3
	10	18.8	19.2	19.8	0.42	18.7	0.65	19	18.9	-0.1
2	11	20.7	20.4	18.7	0.06	15.2	0.00	20.7	20.6	-0.1
	12	19.6	21.8	19.6	0.93	5.6	1	19.9	20.2	+0.3
	13	23.5	22.7	20.8	0.33	23.1	0.06	22.1	22.7	+0.6
	14	19.3	26.8	21.9	0.49	21	0.93	19.3	20.9	+1.6
3	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

context-aware feedback could have an impact on occupant adaptive behaviours and neutral temperatures, and thus meriting further investigation.

- *Hawthorne effect*: This is a phenomenon where people behave differently when they know they are being observed. In this study, we tried to minimize this effect by avoiding instructions on how to use the application. The application was introduced to the students as a tool that they could use to reduce their heating energy use without any additional information on its efficacy. However, as with the fallback effect, only a long-term study is likely to address this problem.

Since the feedback provided includes suggestions for lowering internal temperature, this could potentially have an impact on occupant health especially with older occupants. However, we mitigate this effect by focusing the feedback on temperature ranges within the acceptable band of 18–21°C as suggested by (Jevons et al., 2016).

Finally, this experiment is mainly focusing in detecting changes in thermal comfort variables, namely adaptive actions, neutral temperatures and perceived environmental

Table 2.8: Overall perceived control before (prior) and after (post) the start of feedback; n.a.: not available.

		Overall perceived control		
	No.	prior	post	diff
1a	1	1.5	3.5	+2
	2	2.5	2.5	0
	3	3	3	0
	4	2.5	2.5	0
1b	5	3	3.5	+0.5
	6	2.5	2.5	0
	7	2.5	3	+0.5
	8	3	3.5	+0.5
	9	2.5	4	+1.5
	10	2.5	2.5	0
2	11	2	1.5	-0.5
	12	3.5	3.5	0
	13	3	3	0
	14	2.5	2.5	0
3	15	n.a.	n.a.	n.a.

control. Therefore, results and conclusions of this paper focus on reporting and quantifying those changes, and not other variables such as energy use.

2.6 Conclusions

This study aimed to detect and quantify changes in occupant adaptive responses, neutral temperatures and perceived environmental control as a result of the feedback intervention. From the analysis of the monitored data, it emerges that feedback has the potential to prompt *good* adaptive behaviours such as wearing more clothes and better controlling the use of windows for ventilation, but it also reveals that a risk of high indoor CO_2 levels exists and that, therefore, this problem needs to be carefully addressed when designing feedback strategies. This study also confirms the importance of perceived control in defining thermal comfort and shows that the degree of occupant control over the environment depends not only on the characteristics of the building and of its systems (building contextual factors) but also on occupant awareness of them. Subjects felt they had greater control over their thermal environment and, consequently, this greater control was able to mitigate their thermal expectations and offset possible discomforts due to the lower temperatures. Given a sufficient motivation for interacting with the application, real time feed-back can effectively and positively contribute to guiding occupant adaptive actions towards energy-aware behaviours without negatively affecting their satisfaction. The results of this study therefore demonstrate that saving energy does not always mean sacrificing occupant comfort.

Acknowledgements

This study was jointly supported by the EPSRC-funded ENLITEN project (grant number EP/K002724/1) and a University of Bath Research Scholarship. We would like to thank all the participants and the Exeter City Council for its support provided during the project.

References

ASHRAE. 2013. *Standard 55:2013 – Thermal Environmental Conditions for Human Occupancy (ANSI Approved)*. American Society of Heating, Refrigerating and Air-Conditioning Engineers.

Andersen, I., Lundqvist, G. R., and Proctor, D. F. 1973. Human Perception, of Humidity Under Four Controlled Conditions. *Archives of Environmental Health: An International Journal* 26 (1), pp. 22 – 27. DOI: 10.1080/00039896.1973.10666213.

Ballantyne, E. R., Hill, R. K., and Spencer, J. W. 1977. Probit analysis of thermal sensation assessments. *International Journal of Biometeorology* 21 (1), pp. 29 – 43. DOI: 10.1007/BF01552964.

Boerstra, A., Beuker, T., Loomans, M., and Hensen, J. 2013. Impact of available and perceived control on comfort and health in European offices. *Architectural Science Review* 56 (1), pp. 30 – 41. DOI: 10.1080/00038628.2012.744298.

Bouden, C. and Ghrab, N. 2005. An adaptive thermal comfort model for the Tunisian context: a field study results. *Energy and Buildings* 37 (9), pp. 952 – 963. DOI: 10.1016/j.enbuild.2004.12.003.

Breiman, L. 2001. Random Forests. *Machine Learning* 45 (1), pp. 5 – 32. DOI: 10.1023/A:1010933404324.

Chow, T. T., Fong, K. F., Givoni, B., Lin, Z., and Chan, A. L. S. 2010. Thermal sensation of Hong Kong people with increased air speed, temperature and humidity in air-conditioned environment. *Building and Environment* 45 (10), pp. 2177 – 2183. DOI: 10.1016/j.buildenv.2010.03.016.

Cândido, C., Dear, R. J. de, Lamberts, R., and Bittencourt, L. 2010. Air movement acceptability limits and thermal comfort in Brazil's hot humid climate zone. *Building and Environment* 45 (1), pp. 222 – 229. DOI: 10.1016/j.buildenv.2009.06.005.

Damiati, S. A., Zaki, S. A., Rijal, H. B., and Wonorahardjo, S. 2016. Field study on adaptive thermal comfort in office buildings in Malaysia, Indonesia, Singapore, and Japan during hot and humid season. *Building and Environment* 109, pp. 208 – 223. DOI: 10.1016/j.buildenv.2016.09.024.

De Dear, R. J., Leow, K. G., and Ameen, A. 1991. Thermal comfort in the humid tropics. Part II. Climate chamber experiments on thermal acceptability in Singapore. *Ashrae transactions* 97 (1), pp. 880 – 886.

De Dear, R. J., Brager, G., Reardon, J., Nicol, F., et al. 1998. Developing an adaptive model of thermal comfort and preference/discussion. *ASHRAE transactions* 104, p. 145.

Dear, R. J. de and Brager, G. 2002. Thermal comfort in naturally ventilated buildings: revisions to ASHRAE Standard 55. *Energy and Buildings* 34 (6). Special Issue on Thermal Comfort Standards, pp. 549 – 561. DOI: 10.1016/S0378-7788(02)00005-1.

Dear, R. de, Kim, J., Candido, C., and Deuble, M. 2015. Adaptive thermal comfort in Australian school classrooms. *Building Research & Information* 43 (3), pp. 383–398. DOI: 10.1080/09613218.2015.991627.

Deru, M., Field, K., Studer, D., Benne, K., Griffith, B., Torcellini, P., Liu, B., Halverson, M., Winiarski, D., Rosenberg, M., Yazdanian, M., Huang, J., and Crawley, D. 2011. *U.S. Department of Energy commercial reference building models of the national building stock*. National Renewable Energy Laboratory.

Dhaka, S., Mathur, J., Brager, G., and Honnekeri, A. 2015. Assessment of thermal environmental conditions and quantification of thermal adaptation in naturally ventilated buildings in composite climate of India. *Building and Environment* 86, pp. 17 – 28. DOI: 10.1016/j.buildenv.2014.11.024.

Dhaka, S., Mathur, J., Wagner, A., Agarwal, G. D., and Garg, V. 2013. Evaluation of thermal environmental conditions and thermal perception at naturally ventilated hostels of undergraduate students in composite climate. *Building and Environment* 66, pp. 42 – 53. DOI: 10.1016/j.buildenv.2013.04.015.

Djamila, H., Chu, C.-M., and Kumaresan, S. 2013. Field study of thermal comfort in residential buildings in the equatorial hot-humid climate of Malaysia. *Building and Environment* 62, pp. 133 – 142. DOI: 10.1016/j.buildenv.2013.01.017.

EN. 2007. *EN 15251:2007 – Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics*. European Standard.

Engel, J. 1988. Polytomous logistic regression. *Statistica Neerlandica* 42 (4), pp. 233 – 252. DOI: 10.1111/j.1467-9574.1988.tb01238.x.

Erlandson, T., Cena, K., De Dear, R., and Harvenith, G. 2003. Environmental and human factors influencing thermal comfort of office occupants in hot – Humid and hot – Arid climates. *Ergonomics* 46 (6), pp. 616 – 628. DOI: 10.1080/0014013031000085707.

Fanger, P. O. 1970. *Thermal Comfort*. McGraw-Hill.

Farghal, A. and Wagner, A. 2010. Studying the adaptive comfort model a case study in a hot dry climate, Cairo, Egypt.

Feriadi, H. and Wong, N. H. 2004. Thermal comfort for naturally ventilated houses in Indonesia. *Energy and Buildings* 36 (7), pp. 614 – 626. DOI: 10.1016/j.enbuild.2004.01.011.

Frontczak, M., Schiavon, S., Goins, J., Arens, E., Zhang, H., and Wargocki, P. 2012. Quantitative relationships between occupant satisfaction and satisfaction aspects of indoor environmental quality and building design. *Indoor Air* 22 (2), pp. 119 – 131. DOI: 10.1111/j.1600-0668.2011.00745.x.

Frontczak, M. and Wargocki, P. 2011. Literature survey on how different factors influence human comfort in indoor environments. *Building and Environment* 46 (4), pp. 922 – 937. DOI: 10.1016/j.buildenv.2010.10.021.

Givoni, B., Khedari, J., Wong, N. H., Feriadi, H., and Noguchi, M. 2006. Thermal sensation responses in hot, humid climates: effects of humidity. *Building Research & Information* 34 (5), pp. 496–506. DOI: 10.1080/09613210600861269.

Gómez-Azpeitia, G., Bojórquez-Morales, G., Ruiz, R. P., Marincic, I., González, E., and Tejeda, A. 2012. Extreme adaptation to extreme environments: Case study of hot dry, hot sub-humid, and hot humid climates in Mexico.

Griffiths, I. 1991. *Thermal comfort in buildings with passive solar features: field studies.* The Publications Office of the European Union.

Halawa, E. and Hoof, J. van. 2012. The adaptive approach to thermal comfort: A critical overview. *Energy and Buildings* 51, pp. 101 – 110. DOI: 10.1016/j.enbuild.2012.04.011.

Haldi, F. and Robinson, D. 2010. On the unification of thermal perception and adaptive actions. *Building and Environment* 45 (11), pp. 2440 – 2457. DOI: 10.1016/j.buildenv.2010.05.010.

Hastie, T., Tibshirani, R., and Friedman, J. 2009. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition*. Springer Series in Statistics. Springer New York.

Hilbe, J. 2009. *Logistic Regression Models*. Chapman & Hall/CRC Texts in Statistical Science. Taylor & Francis.

Humphreys, M. A. 1976. Field studies of thermal comfort compared and applied. *Build Serv Eng* 44 (1), pp. 5 – 23.

Humphreys, M. A., Rijal, H. B., and Nicol, J. F. 2013. Updating the adaptive relation between climate and comfort indoors; new insights and an extended database. *Building and Environment* 63, pp. 40 – 55. DOI: 10.1016/j.buildenv.2013.01.024.

Humphreys, M. A., Nicol, J. F., and Raja, I. A. 2007. Field Studies of Indoor Thermal Comfort and the Progress of the Adaptive Approach. *Advances in Building Energy Research* 1 (1), pp. 55–88. DOI: 10.1080/17512549.2007.9687269.

Indraganti, M. 2010a. Thermal comfort in naturally ventilated apartments in summer: Findings from a field study in Hyderabad, India. *Applied Energy* 87 (3), pp. 866 – 883. DOI: 10.1016/j.apenergy.2009.08.042.

Indraganti, M., Ooka, R., and Rijal, H. B. 2013a. Thermal comfort in offices in summer: Findings from a field study under the 'setsuden' conditions in Tokyo, Japan. *Building and Environment* 61, pp. 114 – 132. DOI: 10.1016/j.buildenv.2012.12.008.

Indraganti, M. 2010b. Using the adaptive model of thermal comfort for obtaining indoor neutral temperature: Findings from a field study in Hyderabad, India. *Building and Environment* 45 (3), pp. 519 – 536. DOI: 10.1016/j.buildenv.2009.07.006.

Indraganti, M., Ooka, R., and Rijal, H. B. 2013b. Field investigation of comfort temperature in Indian office buildings: A case of Chennai and Hyderabad. *Building and Environment* 65, pp. 195 – 214. DOI: 10.1016/j.buildenv.2013.04.007.

Indraganti, M., Ooka, R., and Rijal, H. B. 2015. Thermal comfort in offices in India: Behavioral adaptation and the effect of age and gender. *Energy and Buildings* 103, pp. 284 – 295. DOI: 10.1016/j.enbuild.2015.05.042.

Jin, L., Zhang, Y., and Zhang, Z. 2017. Human responses to high humidity in elevated temperatures for people in hot-humid climates. *Building and Environment* 114, pp. 257 – 266. DOI: 10.1016/j.buildenv.2016.12.028.

Jing, S., Li, B., Tan, M., and Liu, H. 2013. Impact of Relative Humidity on Thermal Comfort in a Warm Environment. *Indoor and Built Environment* 22 (4), pp. 598 – 607. DOI: 10.1177/1420326X12447614.

Karyono, T. H. 2008. Bandung thermal comfort study: Assessing the applicability of an adaptive model in indonesia. *Architectural Science Review* 51 (1), pp. 60 – 65. DOI: 10.3763/asre.2008.5108.

Karyono, T. H., Sri, E., Sulistiawan, J. G., and Triswanti, Y. 2015. Thermal comfort studies in naturally ventilated buildings in Jakarta, Indonesia. *Buildings* 5 (3), pp. 917 – 932. DOI: 10.3390/buildings5030917.

Klepeis, N. E., Nelson, W. C., Ott, W. R., Robinson, J. P., Tsang, A. M., Switzer, P., Behar, J. V., Hern, S. C., and Engelmann, W. H. 2001. The National Human Activity Pattern Survey (NHAPS): A resource for assessing exposure to environmental pollutants. *Journal of Exposure Analysis and Environmental Epidemiology* 11 (3), pp. 231 – 252. DOI: 10.1038/sj.jea.7500165.

Kottek, M., Grieser, J., Beck, C., Rudolf, B., and Rubel, F. 2006. World map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift* 15 (3), pp. 259 – 263. DOI: 10.1127/0941-2948/2006/0130.

LACHIREDDI, G. K. K., MUTHUKUMAR, P., and SUBUDHI, S. 2017. Thermal comfort analysis of hostels in National Institute of Technology Calicut, India. $S = adhan = a$ 42 (1), pp. 63 – 73. DOI: 10.1007/s12046-016-0572-x.

Lai, A. C. K., Mui, K. W., Wong, L. T., and Law, L. Y. 2009. An evaluation model for indoor environmental quality (IEQ) acceptance in residential buildings. *Energy and Buildings* 41 (9), pp. 930 – 936. DOI: 10.1016/j.enbuild.2009.03.016.

Liu, H., Wu, Y., Li, B., Cheng, Y., and Yao, R. 2017. Seasonal variation of thermal sensations in residential buildings in the Hot Summer and Cold Winter zone of China. *Energy and Buildings* 140, pp. 9 – 18. DOI: 10.1016/j.enbuild.2017.01.066.

Liu, W., Deng, Q., Ma, W., Huangfu, H., and Zhao, J. 2013. Feedback from human adaptive behavior to neutral temperature in naturally ventilated buildings: Physical and psychological paths. *Building and Environment* 67, pp. 240 – 249. DOI: 10.1016/j.buildenv.2013.05.024.

Luo, M., Cao, B., Zhou, X., Li, M., Zhang, J., Ouyang, Q., and Zhu, Y. 2014. Can personal control influence human thermal comfort? A field study in residential buildings in China in winter. *Energy and Buildings* 72, pp. 411 – 418. DOI: 10.1016/j.enbuild.2013.12.057.

Luo, M., Cao, B., Damiens, J., Lin, B., and Zhu, Y. 2015. Evaluating thermal comfort in mixed-mode buildings: A field study in a subtropical climate. *Building and Environment* 88. Interactions between human and building environment, pp. 46 – 54. DOI: 10.1016/j.buildenv.2014.06.019.

Manu, S., Shukla, Y., Rawal, R., Thomas, L. E., and Dear, R. de. 2016. Field studies of thermal comfort across multiple climate zones for the subcontinent: India Model for Adaptive Comfort (IMAC). *Building and Environment* 98, pp. 55 – 70. DOI: 10.1016/j.buildenv.2015.12.019.

McCullagh, P. 1980. Regression Models for Ordinal Data. *Journal of the Royal Statistical Society. Series B (Methodological)* 42 (2), pp. 109–142.

Mishra, A. K. and Ramgopal, M. 2013. Field studies on human thermal comfort — An overview. *Building and Environment* 64, pp. 94 – 106. DOI: 10.1016/j.buildenv.2013.02.015.

Mishra, A. K. and Ramgopal, M. 2014. Thermal comfort field study in undergraduate laboratories – An analysis of occupant perceptions. *Building and Environment* 76, pp. 62 – 72. DOI: 10.1016/j.buildenv.2014.03.005.

Mishra, A. K. and Ramgopal, M. 2015a. A thermal comfort field study of naturally ventilated classrooms in Kharagpur, India. *Building and Environment* 92, pp. 396 – 406. DOI: 10.1016/j.buildenv.2015.05.024.

Mishra, A. K. and Ramgopal, M. 2015b. An adaptive thermal comfort model for the tropical climatic regions of India (Köppen climate type A). *Building and Environment* 85, pp. 134 – 143. DOI: 10.1016/j.buildenv.2014.12.006.

Moujalled, B., Cantin, R., and Guarracino, G. 2008. Comparison of thermal comfort algorithms in naturally ventilated office buildings. *Energy and Buildings* 40 (12), pp. 2215 – 2223. DOI: 10.1016/j.enbuild.2008.06.014.

Mustapa, M. S., Zaki, S. A., Rijal, H. B., Hagishima, A., and Ali, M. S. M. 2016. Thermal comfort and occupant adaptive behaviour in Japanese university buildings with free running and cooling mode offices during summer. *Building and Environment* 105, pp. 332 – 342. DOI: 10.1016/j.buildenv.2016.06.014.

Nejat, P., Jomehzadeh, F., Taheri, M. M., Gohari, M., and Majid, M. Z. A. 2015. A global review of energy consumption, CO2 emissions and policy in the residential sector (with an overview of the top ten CO2 emitting countries). *Renewable and Sustainable Energy Reviews* 43, pp. 843 – 862. DOI: 10.1016/j.rser.2014.11.066.

Nguyen, A. T., Singh, M. K., and Reiter, S. 2012. An adaptive thermal comfort model for hot humid South-East Asia. *Building and Environment* 56, pp. 291 – 300. DOI: 10.1016/j.buildenv.2012.03.021.

Nicol, F., Jamy, G. N., and Sykes, O. 1994. *A Survey of Thermal Comfort in Pakistan: Toward New Indoor Temperature Standards; Final Report*. School of Architecture, Oxford Brookes Univ.

Nicol, F., Humphreys, M., and Roaf, S. 2012. *Adaptive Thermal Comfort: Principles and Practice*. Taylor & Francis.

Nicol, F. 2004. Adaptive thermal comfort standards in the hot–humid tropics. *Energy and Buildings* 36 (7). Building Research and the Sustainability of the Built Environment in the Tropics, pp. 628 – 637. DOI: 10.1016/j.enbuild.2004.01.016.

Nicol, F. and Humphreys, M. 2010. Derivation of the adaptive equations for thermal comfort in free-running buildings in European standard EN15251. *Building and Environment* 45 (1). International Symposium on the Interaction between Human and Building Environment Special Issue Section, pp. 11 – 17. DOI: 10.1016/j.buildenv.2008.12.013.

Nicol, J. F. and Humphreys, M. A. 2002. Adaptive thermal comfort and sustainable thermal standards for buildings. *Energy and Buildings* 34 (6). Special Issue on Thermal Comfort Standards, pp. 563 – 572. DOI: 10.1016/S0378-7788(02)00006-3.

O'Brien, W. and Gunay, H. B. 2014. The contextual factors contributing to occupants' adaptive comfort behaviors in offices – A review and proposed modeling framework. *Building and Environment* 77, pp. 77 – 87. DOI: 10.1016/j.buildenv.2014.03.024.

Ogbonna, A. C. and Harris, D. J. 2008. Thermal comfort in sub-Saharan Africa: Field study report in Jos-Nigeria. *Applied Energy* 85 (1), pp. 1 – 11. DOI: 10.1016/j.apenergy.2007.06.005.

Olweny, M. R. O., Mugagga, L. L., and Nedala, T. 2016. A study of thermal comfort and thermal preferences in the upland tropical climate of Uganda.

Parsons, K. 2002. *Human Thermal Environments: The Effects of Hot, Moderate, and Cold Environments on Human Health, Comfort and Performance, Second Edition*. Taylor & Francis.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E. 2011. Scikit-learn: Machine Learning in Python. *J. Mach. Learn. Res.* 12, pp. 2825 – 2830.

Pellegrino, M., Simonetti, M., and Fournier, L. 2012. A field survey in Calcutta. Architectural issues, thermal comfort and adaptive mechanisms in hot humid climates.

Pérez-Lombard, L., Ortiz, J., and Pout, C. 2008. A review on buildings energy consumption information. *Energy and Buildings* 40 (3), pp. 394 – 398. DOI: 10.1016/j.enbuild.2007.03.007.

Quinlan, J. R. 1986. Induction of decision trees. *Machine Learning* 1 (1), pp. 81 – 106. DOI: 10.1007/BF00116251.

Rangsiraksa, P. 2006. Thermal comfort in Bangkok residential buildings, Thailand, pp. II541–II546.

Rijal, H. B., Yoshida, H., and Umemiya, N. 2010. Seasonal and regional differences in neutral temperatures in Nepalese traditional vernacular houses. *Building and Environment* 45 (12), pp. 2743 – 2753. DOI: 10.1016/j.buildenv.2010.06.002.

Rijal, H. B. 2014. Investigation of Comfort Temperature and Occupant Behavior in Japanese Houses during the Hot and Humid Season. *Buildings* 4 (3), pp. 437 – 452.

Rijal, H. B., Humphreys, M., and Nicol, F. 2015. Adaptive Thermal Comfort in Japanese Houses during the Summer Season: Behavioral Adaptation and the Effect of Humidity. *Buildings* 5 (3), pp. 1037 – 1054. DOI: 10.3390/buildings5031037.

Rijal, H. B., Humphreys, M. A., and Nicol, J. F. 2017. Towards an adaptive model for thermal comfort in Japanese offices. *Building Research & Information*, pp. 1 – 13. DOI: 10.1080/09613218.2017.1288450.

Sculley, D. 2010. Web-scale K-means Clustering. *Proceedings of the 19th International Conference on World Wide Web*. WWW '10. ACM, pp. 1177 – 1178. DOI: 10.1145/1772690.1772862.

Sharma, M. R. and Ali, S. 1986. Tropical summer index-a study of thermal comfort of Indian subjects. *Building and Environment* 21 (1), pp. 11–24. doi: 10.1016/0360-1323(86)90004-1.

Song, X., Yang, L., Zheng, W., Ren, Y., and Lin, Y. 2015. Analysis on Human Adaptive Levels in Different Kinds of Indoor Thermal Environment. *Procedia Engineering* 121. The 9th International Symposium on Heating, Ventilation and Air Conditioning (ISHVAC) joint with the 3rd International Conference on Building Energy and Environment (COBEE), 12-15 July 2015, Tianjin, China, pp. 151 – 157. doi: 10.1016/j.proeng.2015.08.1042.

Sterling, E. M., Arundel, A., and Sterling, T. D. 1985. Criteria for human exposure to humidity in occupied buildings. Vol. 91. (pt 1B), pp. 611 – 622.

Thapa, S., Bansal, A. K., and Panda, G. K. 2016. Adaptive thermal comfort in the two college campuses of Salesian College, Darjeeling – Effect of difference in altitude. *Building and Environment* 109, pp. 25 – 41. doi: 10.1016/j.buildenv.2016.09.013.

Toe, D. H. C. and Kubota, T. 2013. Development of an adaptive thermal comfort equation for naturally ventilated buildings in hot–humid climates using ASHRAE RP-884 database. *Frontiers of Architectural Research* 2 (3), pp. 278 – 291. doi: 10.1016/j.foar.2013.06.003.

Webb, C. G. 1959. An analysis of some observations of thermal comfort in an equatorial climate. *British journal of industrial medicine* 16, pp. 297 – 310.

Wong, L. T., Mui, K. W., and Hui, P. S. 2008. A multivariate-logistic model for acceptance of indoor environmental quality (IEQ) in offices. *Building and Environment* 43 (1), pp. 1 – 6. doi: 10.1016/j.buildenv.2007.01.001.

Yan, H., Mao, Y., and Yang, L. 2017. Thermal adaptive models in the residential buildings in different climate zones of Eastern China. *Energy and Buildings* 141, pp. 28 – 38. doi: 10.1016/j.enbuild.2017.02.016.

Yang, D., Xiong, J., and Liu, W. 2017. Adjustments of the adaptive thermal comfort model based on the running mean outdoor temperature for Chinese people: A case study in Changsha China. *Building and Environment* 114, pp. 357 – 365. doi: 10.1016/j.buildenv.2016.12.038.

Yang, W. and Zhang, G. 2008. Thermal comfort in naturally ventilated and air-conditioned buildings in humid subtropical climate zone in China. *International Journal of Biometeorology* 52 (5), pp. 385–398. doi: 10.1007/s00484-007-0133-4.

Ye, X. J., Zhou, Z. P., Lian, Z. W., Liu, H. M., Li, C. Z., and Liu, Y. M. 2006. Field study of a thermal environment and adaptive model in Shanghai. *Indoor Air* 16 (4), pp. 320 – 326. doi: 10.1111/j.1600-0668.2006.00434.x.

Zhang, Y., Zhang, J., Chen, H., Du, X., and Meng, Q. 2014. Effects of step changes of temperature and humidity on human responses of people in hot-humid area of China. *Building and Environment* 80, pp. 174 – 183. doi: 10.1016/j.buildenv.2014.05.023.

Postscript

The work done in this Chapter while processing and analysing the collected thermal comfort data has allowed to better understand the statistical methods used in adaptive thermal comfort research and to critically reflects on their limitations and problems. In particular, this work has shown the limitations of the use of linear regression and of the Griffiths method to derive occupant neutral temperatures. In order to overcome some of these limitations, a new method has been introduced to define neutral temperatures. However, even this method is not able to fully account for the complex mechanisms of thermal adaptation of the participants.

The concept itself of neutral temperature suffers some inherent limitations: a comfort temperature range rather than a single-point neutral temperature appears to be a better way to model occupant adaptive thermal comfort.

These reflections are further developed in the next Chapter where thermal comfort data are collected as part of an additional field work and are analysed by using a different statistical technique (logistic regression). Compared to linear regression, logistic regression is more suitable to model the thermal comfort response of the participants, especially when this response is monitored in terms of thermal sensation votes.

Chapter 3

Overheating in vulnerable and non-vulnerable households

Abstract

As the 2003 European heatwave demonstrated, overheating in homes can cause wide-scale fatalities. With temperatures and heatwave frequency predicted to increase due to climate change, such events can be expected to become more common. Thus, investigating the risk of overheating in buildings is key to understanding the scale of the problem and in designing solutions. Most work on this topic has been theoretical and based on lightweight dwellings that might be expected to overheat. By contrast, this study collects temperature and air quality data over two years for vulnerable and non-vulnerable UK homes where overheating would not be expected to be common. Overheating was found to occur, particularly and disproportionately in households with vulnerable occupants. As the summers in question were not extreme and contained no prolonged heatwaves, this is a significant and worrying finding. The vulnerable homes were also found to have worse indoor air quality. This suggests that some of the problem might be solved by enhancing indoor ventilation. The collected thermal comfort survey data were also validated against the European adaptive model. Results suggest that the model underestimates discomfort in warm conditions, having implications for both vulnerable and non-vulnerable homes.

Preamble

This chapter addresses **R**esearch **Q**uestion **2** and aims at understanding the ability of the European adaptive thermal comfort model of predicting the comfort of residential building occupants in UK. As the thermal comfort data are collected in UK, the European adaptive model is here used as main reference for the comparative analysis.

Also this research was carried out within the EPSRC-funded ENLITEN project. As part of this project, low-cost Arduino-based sensors were developed for real-time monitoring of social housing in Exeter, UK. This large monitoring effort resulted in a comprehensive database of environmental, CO_2 and occupancy data and metadata. This chapter describes and reports the results obtained by analysing a part of the ENLITEN dataset collected over a 3-year monitoring period. In particular, the analysis focuses on the assessment of overheating, air quality and occupant thermal comfort in the first two monitored summers (2014 and 2015). This work represents the second thermal comfort field study performed over the course of this PhD.

Most of the work was spent in cleaning and correctly handling the environmental and air quality data as there were many missing and faulty values due to issues with wireless connections and/or due to the inappropriate siting of sensors (e.g., near sources of heat, such as fridges, televisions), etc. Thus, the recorded data needed to be cleaned and validated. This process resulted in a loss of 42% of the available data during summer 2014 and 41% of the available data during summer 2015 with the majority of the losses being in kitchens where the sensors were mainly sited in proximity of the fridges and they were therefore affected by their released heat.

Before the commencement of the data collection, ethical approval was sought and obtained from the research ethics committee of the Department of Psychology of the University of Bath. All the participants signed a consent form at the beginning of the study in which they were assured that their data were treated confidentially and that they could withdraw from the research at any stage.

This Chapter is totally based on a same-titled paper published in Building Research & Information in 2016, more details are provided in the next section.

All data created and used for this study are openly available from the University of Bath data archive at 10.15125/BATH-00203.

Declaration of Authorship

<table>
<tr><td colspan="2">This declaration concerns the article entitled:

Overheating in vulnerable and non-vulnerable households</td></tr>
<tr><td>Status</td><td>Published in the Special Issue of Building Research & Information "Overheating in Buildings: Adaptation Responses".</td></tr>
<tr><td>Details</td><td>Marika Vellei, Alfonso P. Ramallo-González, David Coley, Jeehang Lee, Elizabeth Gabe-Thomas, Tom Lovett & Sukumar Natarajan, Overheating in vulnerable and non-vulnerable households, Building Research & Information, 2016, Volume 45, Issue 1-2, Pages 102-118, ISSN 0961-3218.

DOI: 10.1080/09613218.2016.1222190</td></tr>
<tr><td>Authors' contribution</td><td>The author of this thesis has primarily (85%) contributed to defining the methodology adopted in this work and to writing the manuscript. Regarding the collection of the data: while the thermal comfort telephone interviews and the installation of the CO_2 sensors have mostly been carried out by the author of this thesis, the installation of the other sensors and the initial surveys have been conducted by researchers full-time employed in the ENLITEN project (A. P. Ramallo-González, J. Lee, E. Gabe-Thomas and T. Lovett). Processing and statistical analysis of data have been entirely (100%) carried out by the author of this thesis using the programming language Python. Each author's exact contributions to the article is outlined below:

M. Vellei: Formulation of ideas (85%), Design of methodology (85%), Collection of data (15%), Processing/Analysis of data (100%), Preparation of the manuscript (85%).

A. P. Ramallo-González, J. Lee, E. Gabe-Thomas and T. Lovett: Collection of data (85%).

D. Coley and S. Natarajan: Formulation of ideas (15%), Design of methodology (15%), Editing drafts of manuscript (15%).</td></tr>
<tr><td>Statement from Candidate</td><td>This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.</td></tr>
<tr><td>Date and Signature</td><td></td></tr>
</table>

3.1 Introduction

Although there is not yet a universal definition of what constitutes a *heatwave*, it can be described as a period in which high outdoor temperatures persist for several consecutive days, and night temperatures do not decrease enough to allow buildings to cool down. The European heatwave of August 2003 is estimated to have caused 70,000 excess deaths (Robine et al., 2008), including 2,000 in the UK (Johnson et al., 2005), with the majority of victims being among the elderly and long-term sick.

Global average surface temperatures are predicted to rise by as much as 5°C by 2100 (Stocker, 2013), and heatwaves are expected to increase in intensity, frequency and duration (Jones et al., 2008; Meehl and Tebaldi, 2004; Murphy et al., 2009). In dense urban environments, the consequences of global warming will be exacerbated by the urban heat island effect (Gabriel and Endlicher, 2011; Hondula et al., 2012; Laaidi et al., 2012; Smargiassi et al., 2009). All together this could severely increase levels of thermal discomfort and could lead to an increase in heat-related morbidity and mortality – even in temperate climates such as those normally experienced in the UK.

At the same time, concerns over climate change and the need to implement mitigation strategies are driving the call for a more energy-efficient built environment. The UK Committee on Climate Change (CCC) has set a target of a 20% reduction in energy consumption for space heating by 2030 (CCC, 2012). As a result, super-insulated and airtight houses are currently being built, or existing dwellings are being refurbished to higher thermal standards, in order to reduce winter space heating demand and associated greenhouse gas emissions (Hamilton et al., 2014). So far, much of the adoption of such domestic energy-efficiency measures in the UK has been achieved in newly built homes or refurbished social dwellings, which are supposed to be driving the changes to the UK built environment (Hamilton et al., 2014; DBIS, 2010; McManus et al., 2010).

There is already some evidence of *overheating* happening in British and northern European homes that have been refurbished or newly built in order to comply with the new energy efficiency and zero-carbon standards, e.g., passive social housing flats in Coventry, UK (Tabatabaei Sameni et al., 2015), passive houses in Linköping, Sweden (Rohdin et al., 2014), and low-energy single-family houses in Pays-de-la-Loire, France (Mickaël et al., 2014). To some, the evidence is so clear that a UK national report has been written describing interventions to improve energy efficiency that can prevent overheating in the future (Dengel and Swainson, 2012). However, it is still unclear if any such overheating is due to increases in insulation and airtightness, rather than increases in solar gains (from larger windows) and lower thermal mass. Most importantly, it is not known if it is just a question of occupant behaviour and could therefore be mitigated by educating occupants on the better use of windows and/or by installing mechanical ventilation.

A plethora of studies have used dynamic thermal simulation in order to see how different energy refurbishments might affect building overheating in current and future weather scenarios (Barbosa et al., 2015; Ji et al., 2014; Mavrogianni et al., 2012; McLeod et al., 2013; Oikonomou et al., 2012; Porritt et al., 2011; Porritt et al., 2012; Tillson et al., 2013). However, most of these studies use simple statements of ventilation patterns, e.g., ventilation commencing when the room operative temperature reaches an assumed threshold temperature (Mavrogianni et al., 2012; Porritt et al., 2011; Porritt et al., 2012; Tillson et al., 2013). This is not representative of how windows are used in reality by occupants in homes, since it is based on studies in offices.

The literature offers only a small range of long-term monitoring studies and, therefore, little is known about the current situation of *retrofitted energy-efficient* buildings (Vardoulakis et al., 2015). The most relevant studies are those by Beizaee et al. (2013), Lomas and Kane (2013), Sakka et al. (2012), Tabatabaei Sameni et al. (2015), Wells et al. (2015), White-Newsome et al. (2012), Willand et al. (2016), and Wright et al. (2005). Apart from the link between overheating and ventilation, ventilation is important of itself. With increased airtightness there is a risk of *poor indoor air quality* unless occupants respond appropriately (Yu and Kim, 2012). Again, few data on indoor air quality in energy-efficient buildings exists (Derbez et al., 2014) and this risk is still poorly understood (Wells et al., 2015).

Even less is known about any distinctions between *vulnerable* and *non-vulnerable* households in terms of either the temperatures within their homes or the ventilation patterns they choose (Hoof et al., 2010; Tweed et al., 2015; White-Newsome et al., 2012).

In this study, vulnerable households included one or more occupants falling into one or more of the following categories:

- older than 65 years old,
- disabled,
- with long-term illnesses.

This classification reflects the household types defined in the English Housing Survey (DCLG, 2015a).

Additionally, non-vulnerable homes were classified, based on the number of occupants, as *overcrowded* (more than or equal to five occupants) or *non-overcrowded* homes (fewer than five occupants). This definition of overcrowding is related to the number of occupants rather than to the density of occupants in each dwelling. The monitored dwellings were quite homogeneous in terms of kitchen and living room floor areas and, therefore, the number of occupants was considered better suited to characterize internal heat gains in these spaces. Defining overcrowding in the monitored bedrooms was more difficult since their occupancy (how many people were sleeping in each bedroom) could not be assessed. Therefore, for bedrooms, overcrowding was also defined based on the total number of occupants in each dwelling.

Reduced physical mobility, social isolation and security concerns are some of the reasons that might impede the response of vulnerable occupants to high indoor temperatures and make them at a higher risk of overheating and poor indoor air quality.

Another issue is that existing thermal comfort standards used to quantify the severity and frequency of overheating have not been derived from direct assessments of homes.

The BS EN 15251 adaptive thermal comfort model, upon which the overheating recommendation of the UK Chartered Institution of Building Services Engineers (CIBSE) is based (CIBSE, 2015), has been deduced from data predominantly obtained from field studies in office buildings where people have less opportunity to adapt (Nicol and Humphreys, 2010). This suggests that the applicability and validity of the BS EN 15251 adaptive thermal comfort standard need to be tested with thermal comfort field studies in homes.

Given this background, this paper attempts to provide data to start answering a series of simple questions:

- Do measured data from social housing in the UK indicate that overheating is already occurring?
- Are there any differences between vulnerable and non-vulnerable households?
- Do vulnerable and non-vulnerable households show different attitudes to ventilation and thermal comfort?
- Might any additional overheating (if any) in vulnerable households be explained by reduced ventilation rates, and might increasing the ventilation rate be a potential solution?
- Do long-term measurements of summertime CO_2 in social housing indicate poor air quality?
- Are the existing thermal comfort models able to predict occupant thermal comfort in residential homes in the UK?

In order to do this, the temperature of living rooms, kitchens and bedrooms of 55 newly retrofitted (i.e., reasonably well-insulated) low-rise social dwellings in Exeter, in the south-west of the UK, were monitored during the summers of 2014 and 2015. Additionally, radiator temperatures were monitored (to see if heating might be the cause of any overheating) and CO_2 levels were also monitored (as indicators of air quality). Occupant thermal comfort was investigated through paper-based questionnaires and telephone interviews.

This study can be distinguished from previous large-scale and long-term monitoring studies of summertime temperatures, i.e. (Beizaee et al., 2013; Lomas and Kane, 2013), because it collects radiator temperatures, indoor CO_2 concentrations and thermal comfort responses along with air temperatures.

3.2 Factors affecting overheating

Occupant behavioural thermal adaptation refers to all the conscious or unconscious actions that a person can take in order to modify the building indoor environment or their personal situation. In reducing temperatures and hours of overheating, Coley et al. (2012) found, via dynamic simulation, that occupant behavioural adaptation (e.g., night cooling achieved by opening windows, or closing windows when the external temperature is greater than the internal) is equally important to common structural adaptations (e.g., increased thermal mass, external shading above windows, solar-control glasses and reduced electrical gains by using more energy-efficient items). However, behavioural adaptation is related to the specific characteristics of the occupants, e.g., elderly occupants and those with compromised health might have a limited control of ventilation due to restricted possibility of movement. Since overheating depends on both occupants and dwelling characteristics, the social and behavioural factors interweave with structural aspects making it particularly difficult to assess its causes. This suggests that it is important to know if there are behavioural differences between different social groups.

Various studies have hinted at reasons why overheating might occur:

- Urbanization and the associated urban heat island effect increase ambient temperatures and prevent the cooling of buildings at night. It also influences occupant ventilation patterns, especially night ventilation due to outdoor pollution, noise and for security reasons (Mavrogianni et al., 2012).
- Upper stories, a southern orientation and an elevated glazing-to-wall ratio increase the severity of solar gains (McLeod et al., 2013; Porritt et al., 2012).
- The absence of window shading (fixed external shading devices or external shutters) also makes the dwellings more exposed to solar heat gains (McLeod et al., 2013; Porritt et al., 2012).
- Greater overcrowding implies greater internal heat gains, while increased insulation and air-tightness and a reduced external wall area-to-volume ratio prevent the release of the accumulated heat (Beizaee et al., 2013).
- Properties of the windows. The window opening type (side hung, bottom hung, sliding, etc.), size and controllability also influence the effectiveness of natural ventilation in dissipating the accumulated heat (Roetzel et al., 2010).
- If there is a drop in night temperatures and a sufficient night ventilation of the building, the use of thermal mass can help to reduce peak daytime temperatures by absorbing heat gains during the day and releasing them at night (Peacock et al., 2010). In different circumstances, thermal mass can lead to an increase in the length of heat exposure by retaining heat within the dwelling.

The limited empirical evidence indicates that properties with an elevated risk of overheating are: flats (Beizaee et al., 2013; Lomas and Kane, 2013; Wright et al., 2005) and, especially, top-floor flats (Beizaee et al., 2013); post-1990 British dwellings and, especially, those with insulated cavity walls (Beizaee et al., 2013); and Australian 6-Star-rated homes when compared with lower rated homes (Willand et al., 2016). However, it is quite possible that this list is more indicative of what has been studied rather than where the problem actually resides. In addition, bedrooms have been found to be more susceptible to overheating than living rooms (Firth and Wright, 2008).

The homes used in this study have been selected because they are:

- *medium weight*: insulated external cavity walls of brick, and brick/block internal walls,
- *not over-glazed*: a glazing-to-wall area ratio for each façade of less than 20%,
- *low-rise* with the tallest apartment block consisting of only four floors, and most dwellings being two floors (see Section 3.5.2),

- located *within a maritime climate and on the outskirts of a small city*: therefore they are not greatly affected by an urban heat island (see Section 3.5.4).

Thus, the study has been designed (unlike others) to make the chances of detecting overheating most unlikely. Therefore, if overheating is detected in these properties, it can be concluded reasonably confidently that overheating is more common than previously thought.

3.3 Social housing context

Social homes represent 17% of the total number of houses in the UK (DCLG, 2015b). There are some characteristics of social houses that might make them at a higher risk of overheating now and in future, and of the problems that overheating might cause:

- social homes have the highest rate of occupancy in the country (DCLG, 2015b), which implies higher internal heat gains,
- their tenants disproportionally belong to higher age bands; it is estimated that 22% of the households with a person aged over 65 lives in social homes (ONS, 2011), which implies that they are more vulnerable to heat exposure.

3.4 CIBSE TM52 adaptive thermal comfort benchmark

In order to assess overheating, it is possible to use either *fixed* or *adaptive* criteria. The *Passivhaus criterion*, for example, assumes a fixed temperature benchmark: it sets an operative temperature limit of 25°C which should not be surpassed for more than 10% of the total annual occupied hours. CIBSE Guide A sets a fixed temperature limit of 26°C for bedrooms which should not be exceeded at night (CIBSE, 2015).

In contrast, the adaptive overheating criteria of the CIBSE TM52 Overheating Taskforce (CIBSE, 2013) are based on the European adaptive model of thermal comfort (EN, 2007) and are valid for habitable rooms other than bedrooms.

According to the adaptive model, the range of acceptable temperatures in naturally ventilated buildings is larger than in conditioned ones, and comfort temperatures are a function of outdoor air temperatures. The adaptive model is driven by the idea that in free-running buildings there exists a wide band of temperatures within which an occupant can find his/her own optimum given sufficient adaptive opportunities, such as taking off excess clothing, consuming cold food or cold drinks, opening/closing windows or doors, and drawing curtains (Nicol and Humphreys, 2010). While sleeping, occupants have limited abilities to adapt to temperatures higher than 26°C and, therefore, the adaptive model is not applicable to bedrooms.

Within the European adaptive model, the maximum allowable operative temperature T_{max} depends on the outdoor temperature (Nicol and Humphreys, 2010). Two maximum operative temperature limits are given depending on the degree of vulnerability of the occupants:

$$T_{max(CatI)} = 0.33T_{rm} + 20.8 \tag{3.1}$$

$$T_{max(CatII)} = 0.33T_{rm} + 21.8 \tag{3.2}$$

where T_{rm} is the exponentially weighted running mean of the daily mean outdoor air temperature:

$$T_{rm} = \left(1 - \alpha\right)\left(T_{-1} + \alpha T_{-2} + \alpha^2 T_{-3} + \ldots\right) \tag{3.3}$$

where α is a constant whose recommended value is 0.8; T_{-1} is the mean outdoor temperature of the day before the day in question, T_{-2} for the day before that and so on.

Cat(egory) *I* includes particularly fragile and vulnerable occupants. *Cat*(egory) *II* is for normal occupants in new and retrofitted buildings.

According to CIBSE TM52, a room is considered to overheat if any two of the following three criteria fail. Each criterion uses the difference between the actual operative temperature (T_o) and the maximum operative temperature (T_{max}), expressed as ΔT.

Criterion C1 (frequency of overheating):

$$H_e \leq 3\% \text{ of summer occupied hours} \tag{3.4}$$

where summer (in the northern hemisphere) is defined as May – September, and H_e is the hours of exceedance, given by:

$$H_e = \sum_{i=1}^{h} \begin{cases} 1 \text{ if } \Delta T_i \geq 1°\text{C} \\ 0 \text{ otherwise} \end{cases} \tag{3.5}$$

where h is the total number of occupied hours over the summer period.

Criterion C2 (severity of overheating):

$$W_e \leq 6 \text{ in any one summer day} \tag{3.6}$$

where W_e, the weighted exceedance, is given by:

$$W_e = \sum_{i=0}^{3} h_{ei} \Delta T_i \tag{3.7}$$

where h_{ei} is the number of hours for which each ΔT_i (i.e., ΔT = 0°C, ΔT = 1°C, ΔT = 2°C and ΔT = 3°C) is experienced.

Criterion C3 (upper temperature limit):

$$\Delta T \leq 4°\text{C in any one summer hour} \tag{3.8}$$

Figures 3.9 and 3.10 show the overheating analysis results for kitchens and living rooms. The percentages of exceedance shown in the three bars are based on the three overheating criteria explained above:

- The first bar represents the percentage of summer occupied hours during which $\Delta T \geq 1°C$. This percentage should be less than 3%, otherwise criterion C1 fails.
- The second bar represents the percentage of summer days during which $W_e > 6$. This percentage should be 0, otherwise criterion C2 fails.
- The third bar represents the percentage of summer hours during which $\Delta T > 4°C$. This percentage should be 0, otherwise criterion C3 fails.

The adaptive overheating criteria are based on the operative temperature T_o. In this study, as in other monitoring studies (Beizaee et al., 2013; Lomas and Kane, 2013; Sakka et al., 2012; Tabatabaei Sameni et al., 2015; Wells et al., 2015; White-Newsome et al., 2012; Willand et al., 2016), only the dry bulb air temperature has been measured due to the difficulties of long-term monitoring of radiant temperature and air speed. It is therefore assumed that dry bulb temperature is equal to radiant temperature, but this assumption is not always met in indoor spaces, particularly those with a high thermal mass.

Also, although occupancy was detected by using passive infrared (PIR) sensors, it was not possible to infer occupancy profiles for all the monitored rooms reliably since many of the PIR sensors were not working at times or were covered over. Therefore, in common with other monitoring studies (Lomas and Kane, 2013; Tabatabaei Sameni et al., 2015), occupancy for living rooms and kitchens was assumed to be from 09.00 to 22:59 hours, while for bedrooms occupancy was estimated to be from 23.00 to 08:59 hours.

3.5 Methods

3.5.1 Physical measurements

Wireless temperature, CO_2 and motion sensors reported data to a university-hosted database every five minutes for over two years. The manufacturer-stated accuracy of the sensors is given in Table 3.1. This paper investigates the data monitored during the summers of 2014 and 2015 (1 May – 30 September 2014 and 1 May – 30 September 2015).

In common with other experimental studies in occupied homes (Lomas and Kane, 2013), there were occasional issues with wireless connections and/or due to the inappropriate siting of sensors (e.g., near sources of heat, such as fridges, televisions), etc. Thus, the recorded data needed to be cleaned and validated. This involved both automatic and human inspection, which resulted in a loss of 42% of the available sensors during summer 2014 and 41% of the available sensors during summer 2015 (see the supplemental data online) with the majority of the losses being in kitchens. Similar loss rate have been reported in other long-term monitoring studies, e.g., (Lomas and Kane, 2013).

Post-processing of the temperature time series comprised three main steps. (1) Filtering and smoothing the raw time series in order to eliminate outliers and errors due to the influence of nearby appliances. (2) Visually inspecting the time series by comparing hourly indoor temperatures with hourly radiator temperatures, hourly outdoor air temperatures, hourly solar irradiation, indoor CO_2 concentration and occupancy (as given by the PIR sensors, where available). This allowed it also to be determined if sensors were irreversibly

Table 3.1: Sensors.

Parameter	Range	Accuracy
DS18B20 temperature sensor (used for both air and radiator surface temperature measurements)	-10 to 85°C	± 0.5°C
K30 Senseair CO_2 sensor	0 to 5000 ppm	± 30 ppm
HC-SR501 PIR Infrared Motion Sensor	120°, 0 to 7 m	n.a.

affected by heat sources and/or solar radiation, or if they were erroneously placed on the floor. In all cases all data from the sensor were discarded for the whole experiment, not just for the affected period. (3) Only those sensors reporting more than 80% of the time during the hottest months of June – August were selected for analysis. Post-processing of the CO_2 time series consisted of both the first and third steps.

3.5.2 House and household information

Out of a total of 68 monitored dwellings, only 55 homes had at least one sensor reporting during one of the two summers. These 55 dwellings constitute the monitored sample. House and household information for these homes were collected through questionnaires administered to the participants, and by consulting the Exeter City Council database and directly surveying the dwellings (see the supplemental data online). Figure 3.1 shows the distribution of the dwellings type. Figure 3.2 gives details of the demographics of the occupants.

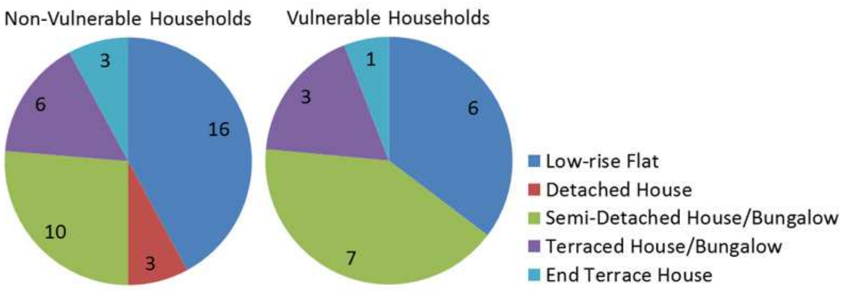


Figure 3.1: Distribution by built type of the 55 monitored dwellings for non-vulnerable and vulnerable households.

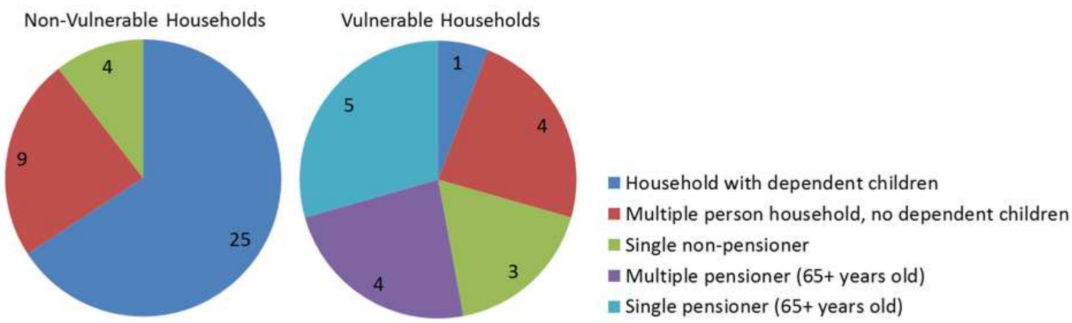


Figure 3.2: Overview of the demographic of the 55 monitored non-vulnerable and vulnerable households.

Among the 55 monitored homes, there were a total of 76 rooms (41 living rooms, 17 kitchens and 18 bedrooms) monitored during summer 2014, and 72 rooms (31 living rooms, 16 kitchens and 25 bedrooms) monitored during summer 2015.

The group of vulnerable households represents 31% of the monitored sample. Non-vulnerable overcrowded homes constitute 18% of the monitored sample. The remaining 51% of the monitored homes includes non-vulnerable and non-overcrowded homes.

Out of 55 dwellings, 52 were built with cavity walls. Unfortunately, there was no information available for the remaining three homes. Also, all the residences were refurbished with double-glazed windows and, when possible, with loft and cavity wall insulation. They were all low-rise dwellings with the tallest apartment block consisting of only four floors. None of the houses was air-conditioned and no windows were shaded (neither fixed external shading devices nor external shutters). All residences were naturally ventilated and all rooms in which data were gathered for the study were equipped with openable windows. Cross-ventilation was theoretically possible in all the dwellings.

Overall, the sample is composed of 22 low-rise flats, 17 semi-detached houses / bungalows, three detached houses, nine mid-terrace houses/bungalows and four end-terrace houses. A total of 18 dwellings were built between 1920 and 1939, 12 between 1940 and 1959, and 24 between 1960 and 1990. The floor area of the dwellings ranges between 42 and 112 m^2, with an average of 84 m^2.

3.5.3 Occupant survey

Occupant surveys were carried out at the end of summer 2014 and during summer 2015. The paper questionnaire administered at the end of summer 2014 included one question about the perceived subjective temperature in summer and two additional questions assessing ventilation and cross-ventilation habits, as reported in Table 3.2. A total of 50 paper questionnaires (16 from vulnerable and 34 from non-vulnerable households) were collected from the monitored homes, i.e., a response rate of 91%.

Additionally, telephone interviews were carried out throughout July – August 2015. The telephone questionnaire was adapted from ASHRAE (2013) and ISO (2005) and included the information reported in Table 3.3. The 20 households who participated in the telephone interviews consisted of 10 vulnerable and 10 non-vulnerable households. Each household was repeatedly surveyed and provided between one and seven questionnaires, for an average of 3.5 responses per household and a total of 70 questionnaires collected.

Table 3.2: Paper questionnaire.

This summer, when the weather was warm, how did you find the temperature in your home?	
1 = Much too cool, 2 = Too cool, 3 = Comfortably cool, 4 = Neither warm nor cool, 5 = Comfortably warm, 6 = Too warm, 7 = Much too warm	
When you open the windows in your home, how often is it for the following reasons?	
To cool your home down	1, 2, 3, 4, 5
To get rid of smells or smoke	1, 2, 3, 4, 5
To get rid of moisture	1, 2, 3, 4, 5
When a room is too stuffy	1, 2, 3, 4, 5
Because you are drying clothes	1, 2, 3, 4, 5
1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, 5 = Always	
How often do you (or someone else in your household) open windows on opposite sides of the building to get a draught flowing through your home?	
1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, 5 = Every day	

Table 3.3: Telephone questionnaire.

Current clothing	Could you generally describe what are you currently wearing?
Activity level	In the last 30 minutes before we started this conversation, how would you describe what you were doing?
Occupied room	In the last 30 minutes before we started this conversation, which room of your home were you in for most of that time?
Thermal sensation vote (TSV)	How are you feeling right now? Measured on the ASHRAE seven-point Likert scale
Thermal preference vote (TPV)	If you could change the current temperature in your home, what would you prefer it to be? Reported on Nicol's scale: –1 (much cooler), –0.5 (a bit cooler), 0 (no change), 0.5 (a bit warmer), 1 (much warmer)
Thermal acceptability vote (TAV)	What do you think about the temperature of your home right now? Reported in the scale: 1 (clearly acceptable), 2 (just acceptable), 3 (just unacceptable), 4 (clearly unacceptable)
Perceived temperature control	How well do you feel that you can control the temperature in your home right now? Reported in the scale: 1 (no control), 2 (light control), 3 (medium control), 4 (high control), 5 (total control)
Sleep quality	At night-time, do you find that it is difficult to sleep because the temperature in your bedroom is too high? Reported in the scale: 1 (not difficult at all), 2 (slightly difficult), 3 (very difficult)

3.5.4 Climate of the study site

The city of Exeter has a population of about 125,000 and a surface area of 47.6 km^2. The Köppen–Geiger climate classification for Exeter is Cfb (Kottek et al., 2006).

For summer 2014, the outdoor temperature was obtained from a mean of the hourly temperatures monitored at six different weather stations located within 5 km from the city centre of Exeter (blue dots in Figure 3.3). For summer 2015, outdoor temperature was directly measured at a station mounted on the roof of a building around the study area (green dot in Figure 3.3). For any time steps when data were not available from the above stations, temperature data from the weather station situated at Exeter Airport (9 km from the city centre – red dot in Figure 3.3) were used. In order to take into account any impact of the urban heat island effect, the data from the airport were corrected using the regression line shown in Figure 3.4, which was obtained by correlating the airport temperatures with those monitored at the weather station within the study area. The regression line shows that when the temperature is low, there are higher temperatures in the city than at the airport. This aligns well with an urban heat island effect. However, when the temperature is high, the temperatures at Exeter Airport are higher than those in the city. This is in contrast with a normal urban heat island effect. Many local effects could be responsible for the temperature being slightly lower in the city than at the airport. Examples are the proximity of a large river (Exe) and green spaces, or the fact that the study weather station is at a higher altitude than the airport, 60.3 and 26.8 metres above mean sea level respectively.

Table 3.4 reports the 30-year averages, covering the period 1981–2010, for the temperatures recorded at the weather station at Exeter Airport (Met Office). While summer

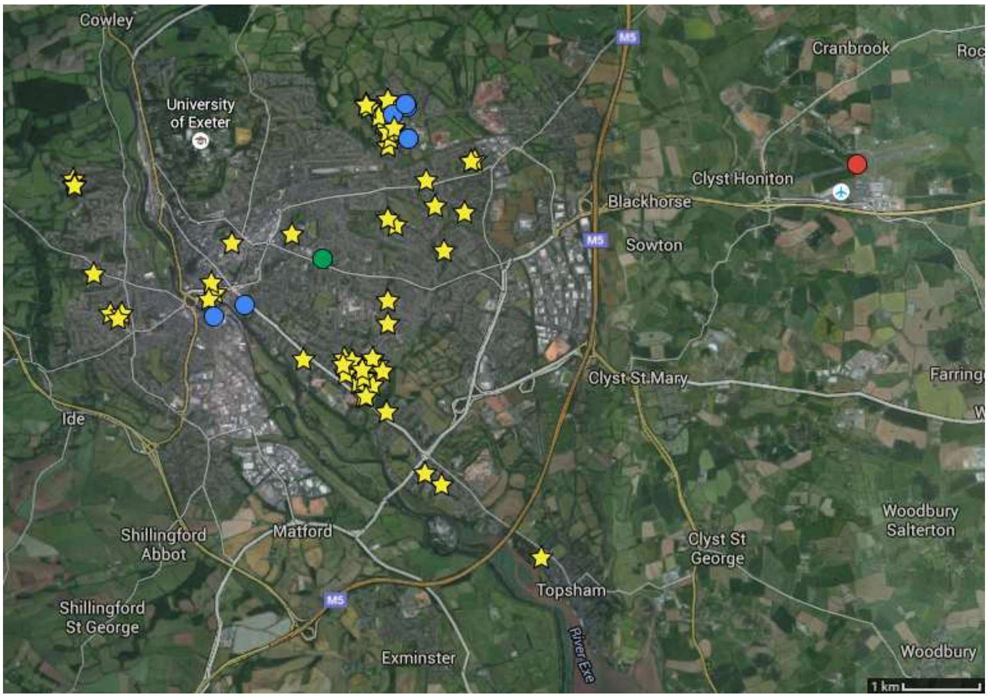


Figure 3.3: Location of the monitored dwellings (yellow stars) and weather stations (blue, red and green dots) in the city of Exeter, southwest UK. Source: Google Maps.

2015 was generally slightly cooler compared with the long-term record and 2014 slightly warmer, neither could be consider atypical or extreme (Figure 3.5). According to the definition of the World Meteorological Organization, a heatwave happens "when the daily maximum temperature of more than five consecutive days exceeds the average maximum temperature by 5°C, the normal period being 1961–1990". Based on the records of the Met Office and the definition of the World Meteorological Organization, neither summer 2014 nor summer 2015 included a heatwave.

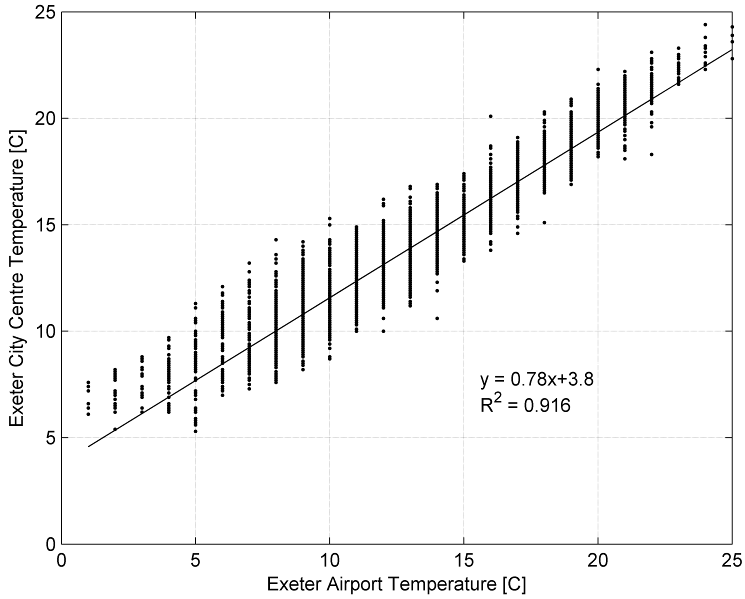


Figure 3.4: Regression line fitted between Exeter city centre and Exeter airport temperatures.

Table 3.4: Historic average meteorological temperatures.

	Averages for 1981–2010			2014	2015
Month	Maximum (°C)	Minimum (°C)	Mean (°C)	Mean (°C)	Mean (°C)
May	16.8	7.6	12.2	13	12.4
June	19.8	10.5	15.15	16.5	15.1
July	21.7	12.4	17.05	18.1	16.5
August	21.5	12.3	16.9	15.7	16.2
September	19.2	10.3	14.75	15.8	13.8

Daily mean, maximum and minimum outdoor temperatures recorded during May – September 2014 are shown in Figure 3.6. It is noteworthy that minimum outdoor temperatures always fell below 18°C, and normally below 15°C. In addition, the mean temperatures, with the exception of a few days, were below 20°C. This suggests that natural ventilation had clear potential for preventing overheating in the study area. This further suggests that

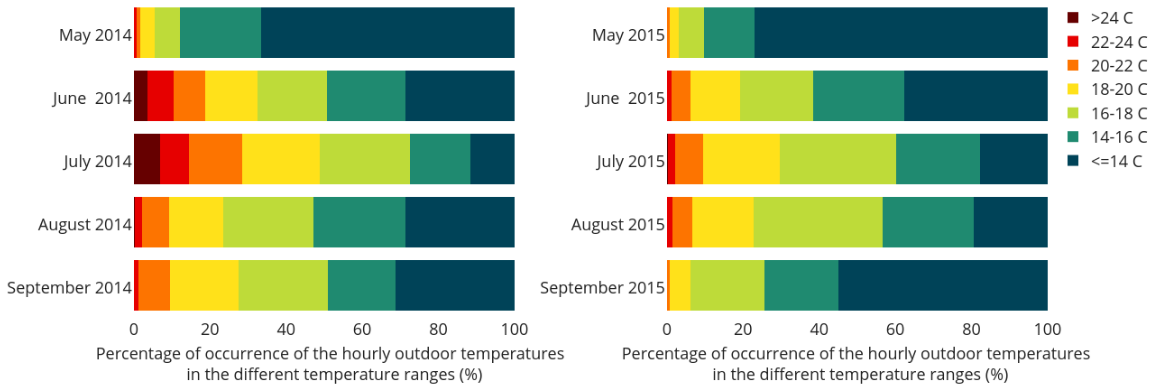


Figure 3.5: Percentage of occurrence of the hourly outdoor temperatures in the different temperature ranges (%).

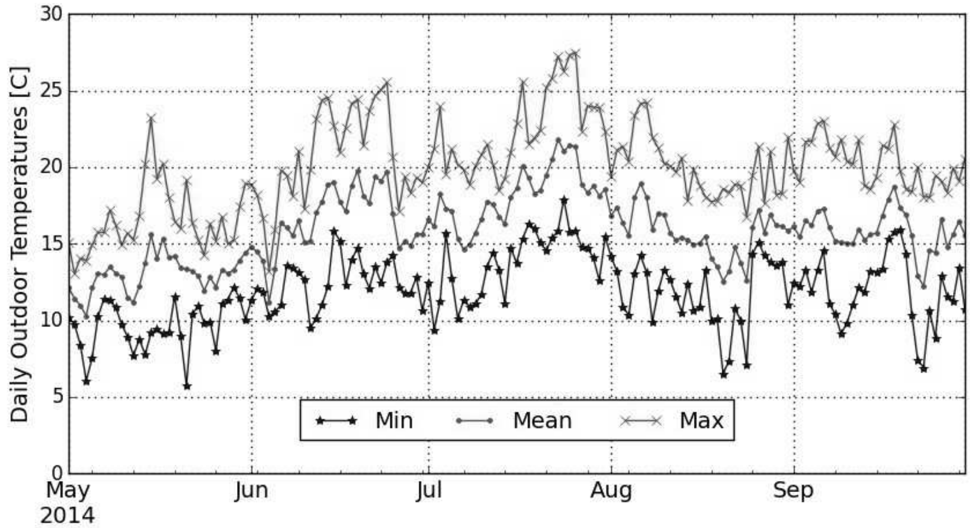


Figure 3.6: Daily minimum, mean and maximum outdoor temperatures, May – September 2014.

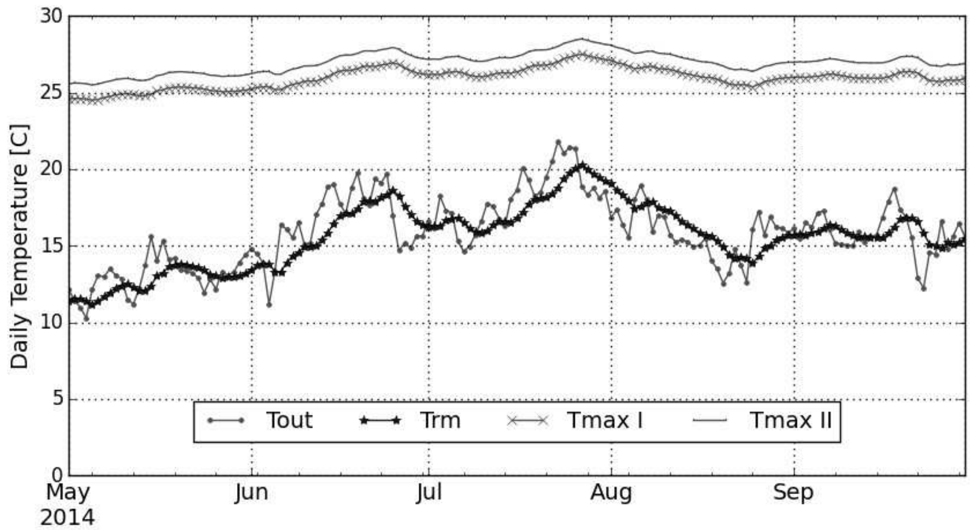


Figure 3.7: Daily mean outdoor temperatures (T_{out}), exponentially weighted running mean of T_{out} (T_{rm}), and maximum allowable temperatures (T_{max}) for Categories I and II, May–September 2014.

any observed overheating is likely to imply low indoor ventilation rates. The exponentially weighted running mean of the daily outdoor air temperature (T_{rm}) and the maximum allowable temperature (T_{max}) for categories I and II are shown in Figure 3.7.

3.6 Results

3.6.1 Indoor temperatures and overheating risk

An unbalanced design four-way analysis of variance (ANOVA) was performed to analyse differences among temperature means (i.e. the means of the mean daily temperatures recorded from 09.00 to 22.00 hours during the hottest months of June – August for summers 2014 and 2015), considering 4 factors: roof exposure, façade orientation, occupant type and room type. The null hypothesis for the four-way ANOVA is that the temperature means are the same for all the groups within each factor.

South-facing rooms (S), i.e. rooms with at least one window façade facing south between 90 and 270°, were tested against the remaining north-facing rooms (N). Roof-exposed rooms (RE) were tested against the remaining rooms in the lower floors (LF). Regarding occupant type, temperatures recorded in rooms of vulnerable and non-vulnerable overcrowded households (V-O) were tested against temperatures monitored in the remaining rooms of non-vulnerable non-overcrowded households (nV-nO). Regarding room type, temperatures recorded in living rooms (Lr) were tested against temperatures monitored in kitchens (K) and those monitored in bedrooms (Br).

Results of the four-way ANOVA for summer 2014 are presented in Figure 3.8; the three factors shown in the plot are roof exposure (RE versus LF), occupant type (V-O versus nV-nO) and room type (K versus Lr versus Br). Descriptive statistics for the mean temperatures monitored during the two summers and results of the ANOVA test are reported in Table 3.5. The significance level α is set at 0.1. If the p-value is above 0.1, then the evidence is not statistically significant. Thus, if the p-value is between 0.1 and 0.05, the evidence is weak, while if the p-value is below 0.05, the evidence is strong. Note that the small size of some of the subsets (Table 3.5) likely had an impact on the statistical power of the ANOVA test.

Roof-exposed (RE) rooms were found to have statistically significantly higher mean daily temperatures than lower-floor (LF) rooms ($p < 0.01$; Table 3.5) during summer 2014, but not during the comparatively cooler summer of 2015. This result is in agreement with the results from other monitoring studies that show that top-floor flats are at a higher overheating risk than lower-floor flats (Beizaee et al., 2013). South-facing rooms were not found to have statistically significantly different mean temperatures than north-facing rooms in either of the two summers.

The highest mean temperatures were recorded in the kitchens during both summers. The difference in the mean temperatures for the three types of rooms is statistically significant for both summers of 2014 and 2015 (Table 3.5).

During summer 2014, rooms in vulnerable and overcrowded dwellings were found to have significantly higher mean temperatures (about 0.6°C) than rooms in non-vulnerable

Table 3.5: Results of the four-way analysis of variance (ANOVA) and descriptive statistics for the two summers.

Factors	Summers	No. of rooms, group 1	No. of rooms, group 2	No. of rooms, group 3	Mean ± SD, group 1 (°C)	Mean ± SD, group 2 (°C)	Mean ± SD, group 3 (°C)	Significance	p-value
S versus N	2014	39	37		23.3 ± 1.5	23.5 ± 1.5		No	0.4
RE versus LF		29	47		24.1 ± 1.5	22.9 ± 1.4		Strong	0.009
V-O versus nV-nO		38	38		23.7 ± 1.4	23.1 ± 1.5		Weak	0.076
K versus Lr versus Br		17	41	18	23.9 ± 1.3	23.1 ± 1.5	23.4 ± 1.7	Weak	0.078
S versus N	2015	35	37		22.6 ± 1.1	22.5 ± 1.4		No	0.5
RE versus LF		33	39		22.7 ± 1.2	22.5 ± 1.3		No	0.42
V-O versus nV-nO		40	32		22.6 ± 1.1	22.5 ± 1.3		No	0.93
K versus Lr versus Br		25	31	16	23.0 ± 1.0	22.2 ± 1.2	22.5 ± 1.4	Strong	0.049

Note: S = rooms with at least one window façade facing south between 90 and 270°; N = remaining rooms facing north; RE = roof-exposed rooms; LF = remaining rooms in the lower floors; V-O = rooms in vulnerable or overcrowded households; nV-nO = remaining rooms in non-vulnerable and non-overcrowded households; Lr = living rooms; Br = bedrooms; K = kitchens.

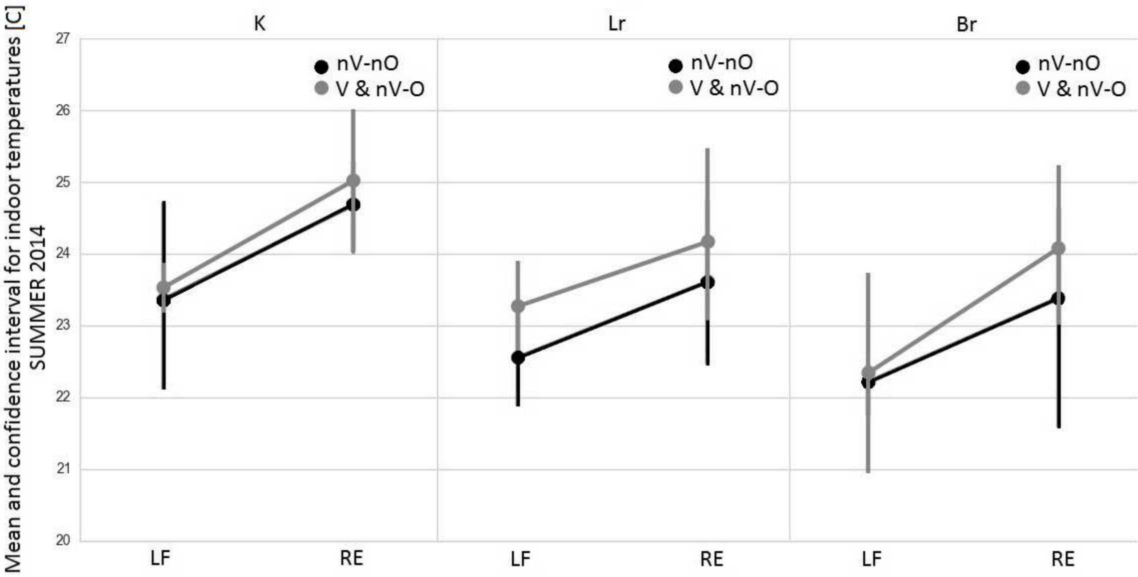


Figure 3.8: Results of the analysis of variance (ANOVA) for summer 2014 for LF (lower floor) and RE (roof exposed) rooms with V-O (vulnerable and non-vulnerable overcrowded) and nV-nO (non-vulnerable non-overcrowded) households.

and non-overcrowded homes (p = 0.076; Table 3.5).

Overheating in living rooms and kitchens was assessed using the CIBSE TM52 adaptive benchmark. Since many of the monitored kitchens included a dining area, they were considered as habitable rooms. No room was found to overheat during summer 2015. During the comparatively warmer summer of 2014, it was found that 18% of the kitchens (i.e., one from non-vulnerable and two from vulnerable households), and 5% of the living rooms (i.e., two from vulnerable households) suffered overheating (Figures 3.9 and 3.10). Kitchens were more exposed to the risk of overheating than living rooms. This is in agreement with the higher mean temperatures found in kitchens (Table 3.5), which may have been due to the high internal heat gains associated with the cooking activities.

From the overheating assessment of bedrooms using the fixed CIBSE criteria of 26°C, four out of 16 bedrooms overheated during summer 2015, while 15 out of 18 rooms overheated during the warmer summer of 2014 (Figure 3.11). The high temperatures of the bedrooms can be explained by the fact that they are mostly located under the roof (74% of the monitored bedrooms are roof-exposed).

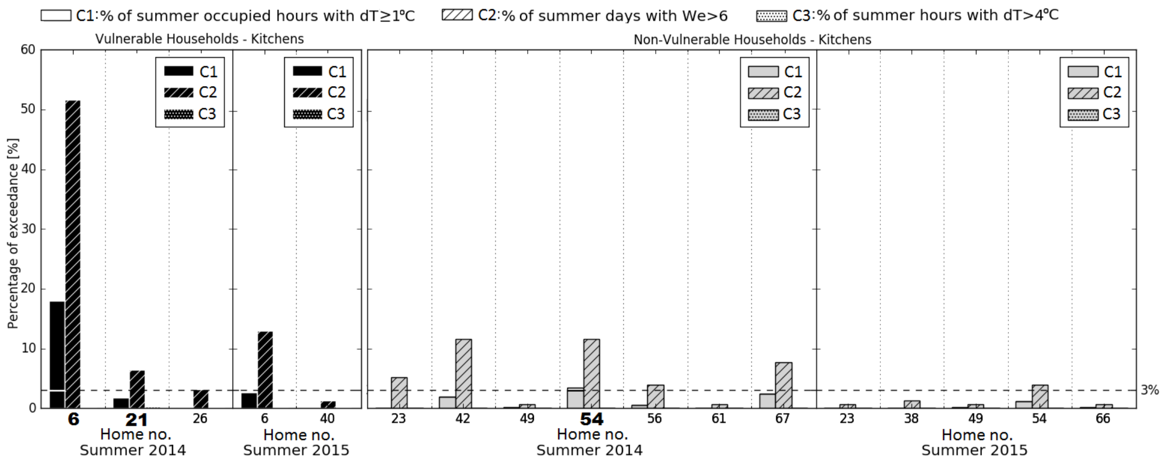


Figure 3.9: Percentage of exceedance for the three criteria (C1–C3) for both Category I (vulnerable households) and Category II (non-vulnerable households) in the monitored kitchens for 2014 and 2015. Only rooms failing at least one criterion are shown. Vulnerable kitchens represent 60% and 25% of the monitored sample in 2014 and 2015 respectively. Non-vulnerable kitchens represent 60% and 30% of the monitored sample in 2014 and 2015 respectively. Overheating rooms are indicated in bold.

Overall, 38% of the monitored vulnerable rooms overheated during summer 2014, while 18% of the non-vulnerable rooms suffered overheating according to the CIBSE fixed criterion (for bedrooms) and the adaptive criteria (for living rooms and kitchens).

By looking at radiator temperatures, more vulnerable homes than non-vulnerable homes tended to keep their heating system on during summer. For summer 2014, 77% of the vulnerable homes (10 out of 13) kept their radiators on, while only 33% of the non-vulnerable homes had their radiators on (8 out of 24). For summer 2015 the situation is similar: 54% of the vulnerable homes (7 out of 13) kept the heater on, while only 21% of the non-vulnerable homes had the radiators on (5 out of 23). These differences provide an important insight into the reasons for overheating in summer, especially for the vulnerable homes.

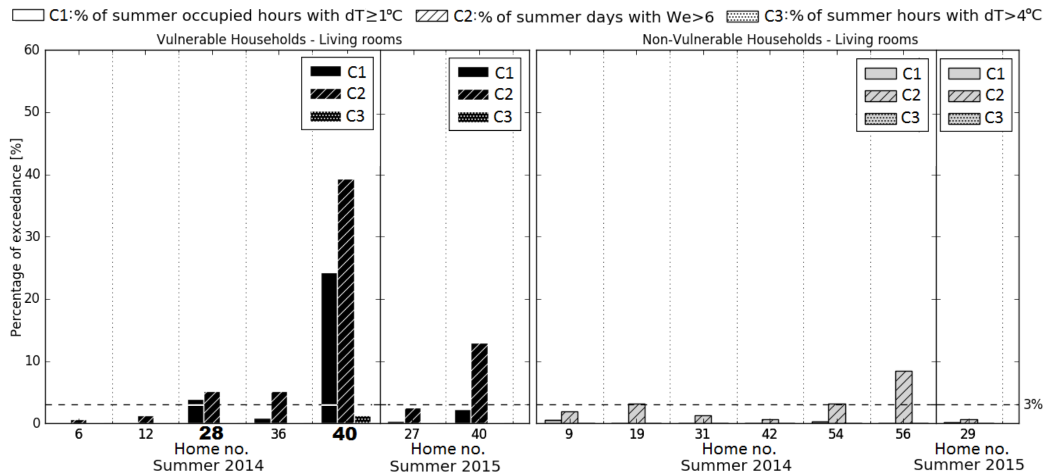


Figure 3.10: Percentage of exceedance for the three criteria (C1–C3) for both Category I (vulnerable households) and Category II (non-vulnerable households) in the monitored living rooms for 2014 and 2015. Only rooms failing at least one criterion are shown. Vulnerable living rooms represent 38% and 20% of the monitored sample in 2014 and 2015 respectively. Non-vulnerable living rooms represent 21% and 5% of the monitored sample in 2014 and 2015 respectively. Overheating rooms are indicated in bold.

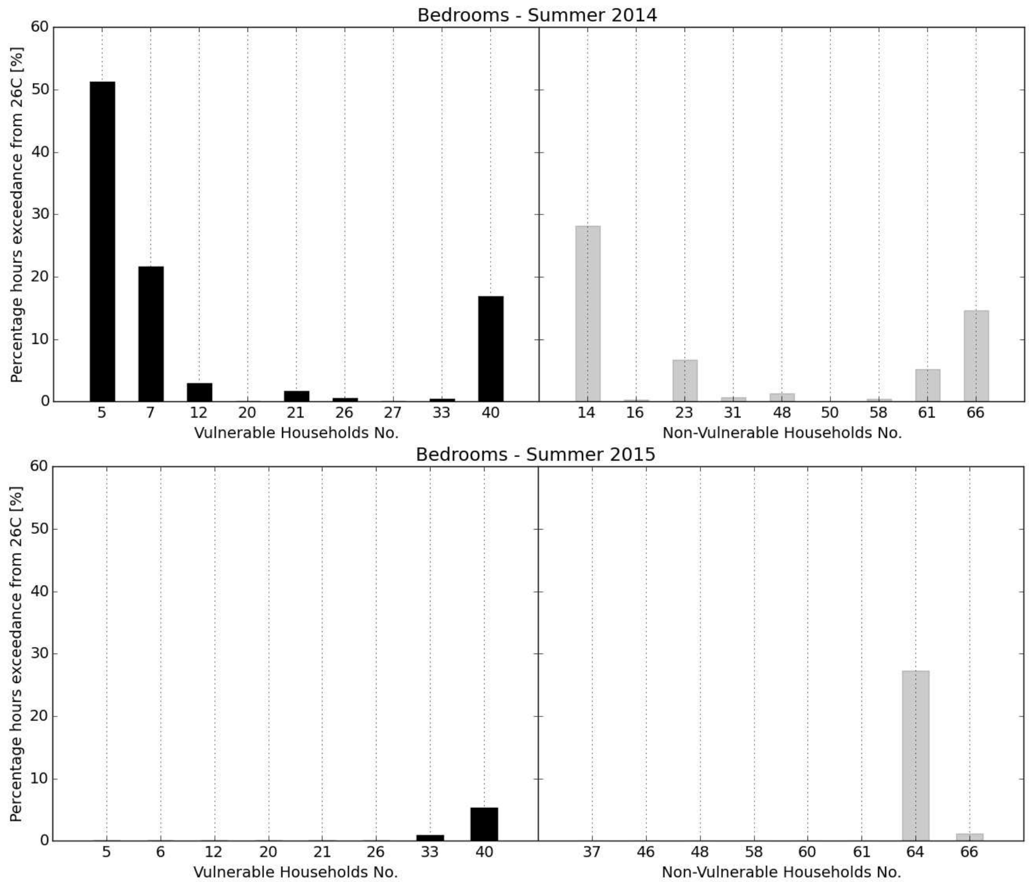


Figure 3.11: Percentage of exceedance from 26°C for both vulnerable and non-vulnerable households in the monitored bedrooms for 2014 (above) and 2015 (below).

3.6.2 Ventilation and indoor air quality

From the ventilation survey, a statistically significant difference between the average ventilation frequency vote of vulnerable and non-vulnerable households was found (Table

Table 3.6: Results of Mann–Whitney tests for ventilation frequency votes, subjective temperature votes and CO_2 concentration.

Groups	Items	Mean ± SD, group 1	Mean ± SD, group 2	Significance	p-value
V versus nV	Ventilation frequency votes	2.6 ± 1.1	3.3 ± 1.2	Strong	1.9E–04
V versus nV	Cross-ventilation frequency votes	2.5 ± 1.3	2.2 ± 1.8	No	0.3
V versus nV	Subjective temperature votes	4.1 ± 1.7	5.4 ± 0.9	Strong	0.01
V versus nV	CO_2 concentration	751 ± 173 ppm	589 ± 94 ppm	Strong	0.007

Note: V = vulnerable households; nV = non-vulnerable households.

3.6) with vulnerable occupants having a tendency to open windows less often. Also, the CO_2 levels recorded in 21 living rooms (10 vulnerable and 11 non-vulnerable households) during June – August 2015 revealed a statistically significant higher mean CO_2 concentration in vulnerable living rooms compared with non-vulnerable ones. This provides a physical confirmation of the survey results (Figure 3.12), and discounts the possibility that the vulnerable occupants are opening the windows less frequently and have the windows more widely open. Figure 3.13 shows that in non-vulnerable homes the recommended limit of 1,000 ppm (ASTM, 2012) for indoor CO_2 concentration was exceeded in only 4% of the monitored hours, which indicates good indoor conditions. However, the situation is quite different in vulnerable homes where the limit of 1,000 ppm is exceeded in 20% of the monitored hours. This is worrying given that occupants are less likely to open windows during winter and, therefore, CO_2 levels can be expected to be even higher and indoor air quality to be worse.

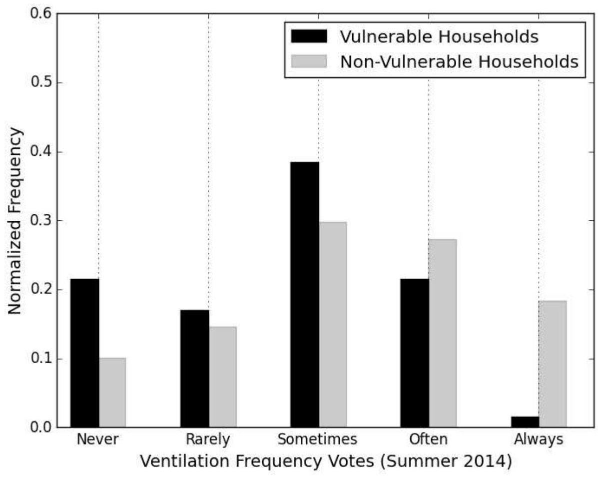


Figure 3.12: Ventilation frequency votes for vulnerable and non-vulnerable households, summer 2014.

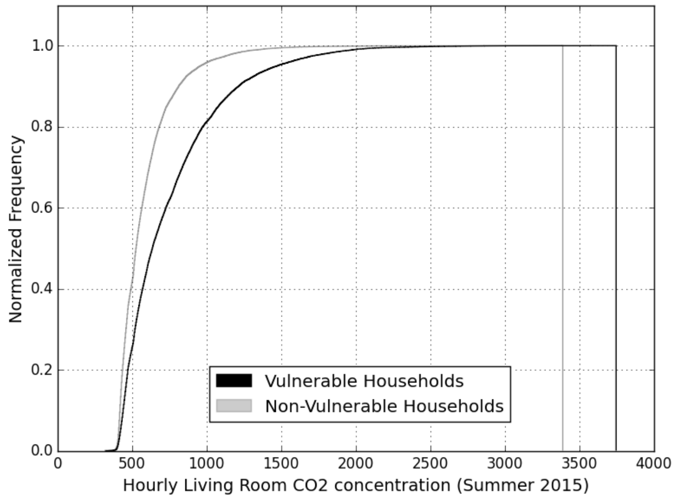


Figure 3.13: Cumulative histogram of hourly monitored CO_2 concentration for vulnerable and non-vulnerable households, summer 2015.

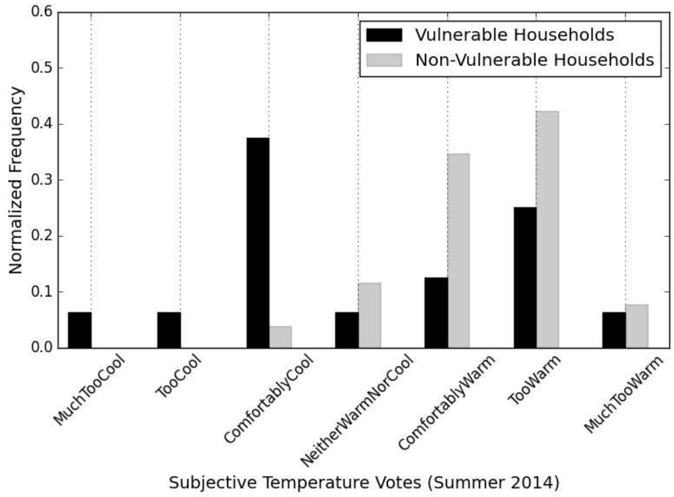


Figure 3.14: Subjective temperature votes for vulnerable and non-vulnerable households, summer 2014.

These findings of significantly different window opening patterns for vulnerable occupants, and a corresponding reduction in air quality, represents an important new insight since occupant age was not found to be a significant driver of window-opening behaviours in previous works (Fabi et al., 2012).

The higher temperatures recorded in vulnerable and overcrowded rooms may have been due to high internal gains (in overcrowded homes) and poor ventilation and radiators on (in vulnerable homes).

3.6.3 Thermal comfort

The analysis of the thermal comfort responses for summer 2014 (see the paper questionnaire in Table 3.2) indicates that vulnerable occupants had the tendency to feel cooler when compared with non-vulnerable occupants (Figure 3.14 and Table 3.6). This is probably why vulnerable occupants decided to keep their radiators on, as noted above. This is dangerous since it could potentially make them less ready to undertake behavioural actions for heat protection.

For the analysis of the thermal comfort responses collected during the telephone interviews (Table 3.3), the mean temperature recorded in the hour preceding the telephone call for the room where the occupants indicated that they spent most of the time was used. If the environmental sensor was not reporting in this room, then the temperature of another room in the home was used when available. The difference dT between that temperature T_{room} and the comfort temperature T_{comf} defined by the European adaptive equation (Nicol and Humphreys, 2010) was then calculated:

$$dT = T_{room} - T_{comf} \tag{3.9}$$

where $T_{comf} = 0.33T_{rm} + 18.8$.

Finally, a logistic regression was fitted using thermal preference (TPV), thermal sensation (TSV) and thermal acceptability votes (TAV) and the calculated dT. Figures 3.16, 3.17 and 3.18 show the fitted logistic models together with the data binned for 1°C of dT. Logistic regression for TPV and TSV are statistically significant (Tables 3.7 and 3.8), while the logistic regression for TAV does not reach statistical significance (see Table 3.9) and it is therefore not considered further in the analysis.

Based on the results from the Smart Controls and Thermal Comfort (SCATs) surveys from 26 European office buildings (Nicol and Humphreys, 2007) at the base of the European adaptive equation, the proportion P of subjects voting *Warm* or *Hot* on the ASHRAE comfort scale is given by the following logistic model (see also Figure 3.15):

$$P = \frac{e^{0.4734dT+2.607}}{1 + e^{0.4734dT+2.607}} \tag{3.10}$$

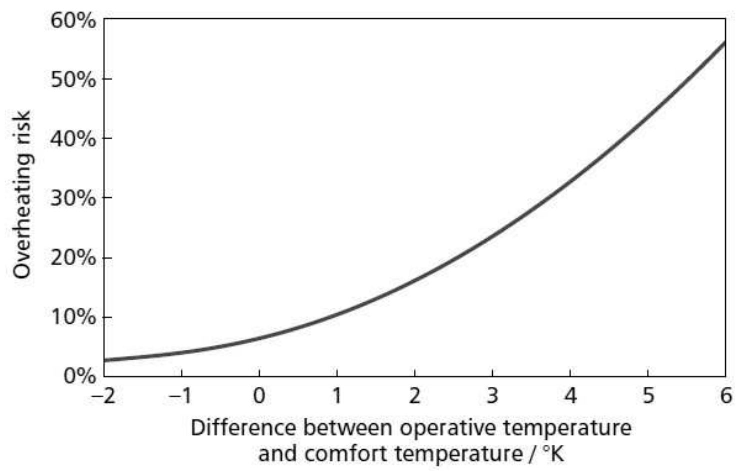


Figure 3.15: Proportion of subjects voting *Warm* or *Hot* on the ASHRAE scale (overheating risk) as a function of the difference dT between indoor operative temperature and comfort temperature. Source: Nicol and Humphreys (2007).

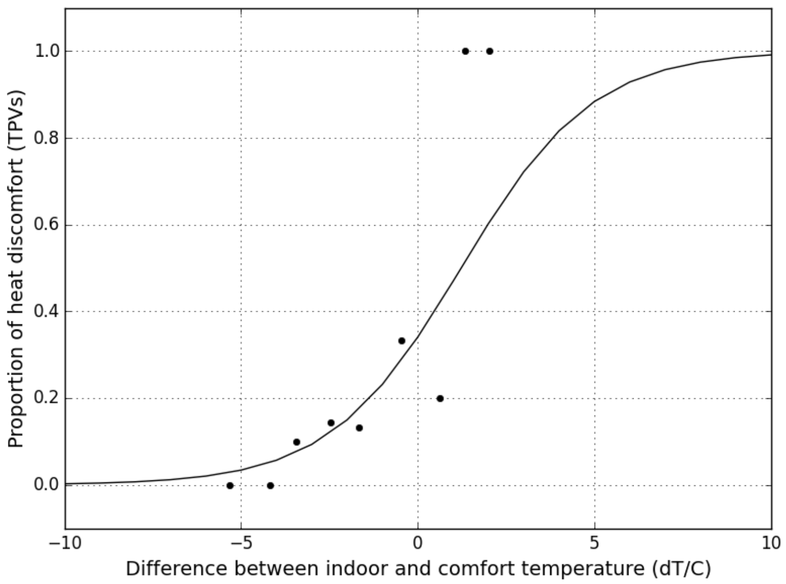


Figure 3.16: Proportion of subjects voting *Much cooler* or *A bit cooler* as a function of the difference *dT* between indoor temperature and comfort temperature.

Table 3.7: Results of the logistic regression fitted using the thermal preference votes (TPVs).

	coef.	SE	p-value	[95.0% conf. int.]
Intercept	-0.6614	0.452	0.144	-1.548 to 0.225
dT	0.5381	0.241	0.026	0.066 to 1.011

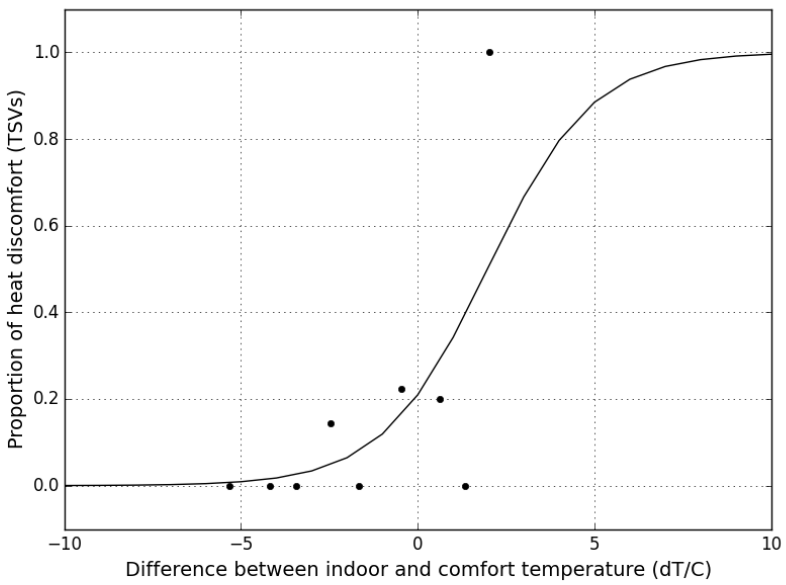


Figure 3.17: Proportion of subjects voting *Warm* or *Hot* as a function of the difference *dT* between indoor temperature and comfort temperature.

Table 3.8: Results of the logistic regression fitted using the thermal sensation votes (TSVs).

	coef.	SE	p-value	[95.0% conf. int.]
Intercept	-1.3276	0.509	0.009	-2.326 to -0.329
dT	0.6734	0.311	0.030	0.064 to 1.283

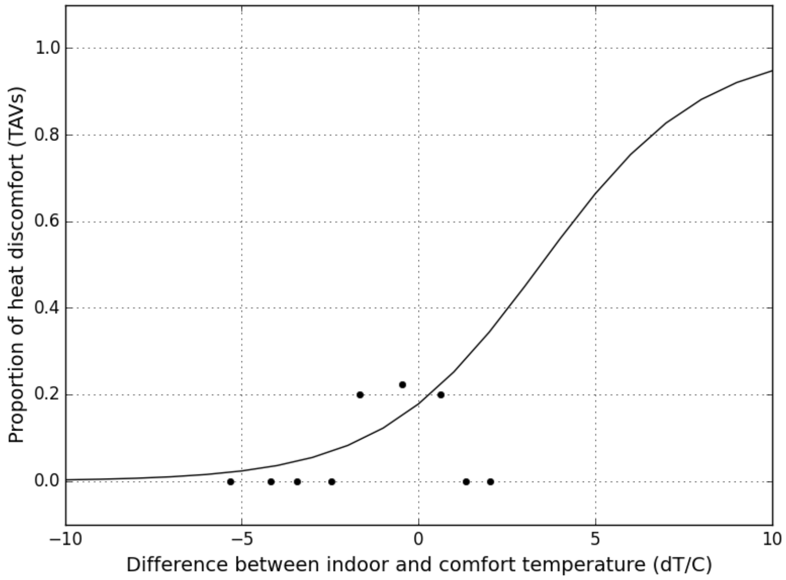


Figure 3.18: Proportion of subjects voting *Just unacceptable* or *Clearly unacceptable* as a function of the difference *dT* between indoor temperature and comfort temperature.

Table 3.9: Results of the logistic regression fitted using the thermal acceptability votes (TAVs).

	coef.	SE	p-value	[95.0% conf. int.]
Intercept	-1.5303	0.534	0.004	-2.577 to -0.483
dT	0.4418	0.287	0.124	-0.121 to 1.005

European adaptive model predictions have been compared against observed discomfort votes given by the fitted logistic regressions, which suggest that at $dT = 0$:

- 35% of the occupants prefer *Much cooler* or *A bit cooler* (Figure 3.16),
- 20% of the occupants voted *Warm* or *Hot*, instead of the 10% predicted by the SCATs logistic model (Figure 3.17),
- If dT is calculated using the maximum allowable operative temperature for vulnerable occupants, i.e., $T_{max(CatI)}$, the proportion of the occupants voting *Just unacceptable* or *Clearly unacceptable* is equal to 35%, which is 15% more than the 20% predicted by the adaptive comfort model.

These results provide new insight on the validity of the European adaptive relation in Europe, suggesting that the adaptive model slightly underestimates occupant thermal discomfort in Exeter. This is not wholly unexpected given that the work on the European adaptive model suggested that people in warm climate zones prefer warmer indoor temperatures than people living in cold climate zones. However, in reality the model is used in a climate-agnostic manner. That is, the model predicts that at a mean outdoor air temperature of 25°C, 80% of occupants will find it thermally acceptable until 29°C – whether in Northern England or Southern Italy. This, and the fact that the underlying data for the model derives primarily from offices, creates difficulties in the application of the model.

3.7 Limitations

This study has the following limitations:

- The distinctions between vulnerable and non-vulnerable households, in terms of either the temperatures within their homes or the ventilation patterns they choose, is based on a relatively small sample of homes. CO_2 levels were recorded during summer 2015 in only 21 living rooms: 10 vulnerable and 11 non-vulnerable households. During summer 2014 temperatures were monitored in 76 rooms, 38 from non-vulnerable homes and 38 from vulnerable and non-vulnerable overcrowded homes. While during summer 2015 temperatures were monitored in 72 rooms, 40 from non-vulnerable homes and 32 from vulnerable and non-vulnerable overcrowded homes.
- The CIBSE adaptive overheating criteria are based on the monitored occupied hours; the fact that occupancy could not be detected implies that overheating predictions based on the model might not be accurate.
- The differences found between vulnerable and non-vulnerable households might have been exacerbated by the monitored sample being social housing. Another study on the same lines but applied to a different social context in the UK could help to demonstrate if any such differences are still present.

3.8 Conclusions

This study investigated overheating, ventilation, thermal comfort and indoor air quality in social dwellings occupied by vulnerable and non-vulnerable households.

Air and radiator temperatures and CO_2 levels were recorded over two summers in 55 homes, and surveys were concurrently administered to the occupants. The homes were carefully selected to be medium weight, not over-glazed, low-rise, within a maritime climate with little risk of being affected by an urban heat island. The only uncontrolled variable, the weather, did not create extreme or atypical conditions that would increase overheating risk.

Despite this, it was observed that:

- overheating occurred even though the study period contained no heatwaves as defined by the Met Office,
- there was a clear difference in the measured frequency of overheating between vulnerable and non-vulnerable households,

- there was a statistically significant difference in the survey-reported attitudes to window use between vulnerable and non-vulnerable households, and this conclusion was supported by CO_2 measurements in the homes,
- CO_2 measurements pointed to poor summertime air quality in vulnerable households,
- the European adaptive model predictions were found to slightly underestimate occupant thermal discomfort.

These results are both worrying and comforting. With 14,000 elderly people dying in Paris during a single heatwave, the confirmed existence of overheating during two typical summers in homes occupied by the vulnerable is a great cause for concern. The experiment was deliberately designed through the choice of its location and type of building to make overheating unlikely, yet it was found in 38% of the vulnerable homes.

The discovery that reduced levels of ventilation in vulnerable homes is a major contributor to this overheating is good news, as it points to a possible strategy. As the experiment contained a control group (the non-vulnerable households) living in near-identical homes, the experiment also shows that these increased ventilation rates can be achieved through behavioural change without alterations to the homes. These changes entail zero capital cost.

Acknowledgements

This study was jointly supported by the EPSRC-funded ENLITEN project (grant number EP/K002724/1) and a University of Bath Research Scholarship.

References

ASHRAE. 2013. *Standard 55:2013 – Thermal Environmental Conditions for Human Occupancy (ANSI Approved)*. American Society of Heating, Refrigerating and Air-Conditioning Engineers.

ASTM. 2012. *ASTM D6245:2012 – Standard Guide for Using Indoor Carbon Dioxide Concentrations to Evaluate Indoor Air Quality and Ventilation*. ASTM International.

Barbosa, R., Vicente, R., and Santos, R. 2015. Climate change and thermal comfort in Southern Europe housing: A case study from Lisbon. *Building and Environment* 92, pp. 440 – 451. DOI: 10.1016/j.buildenv.2015.05.019.

Beizaee, A., Lomas, K. J., and Firth, S. K. 2013. National survey of summertime temperatures and overheating risk in English homes. *Building and Environment* 65, pp. 1 – 17. DOI: 10.1016/j.buildenv.2013.03.011.

CCC. 2012. *Meeting carbon budgets – 2012 progress report to parliament*. UK Committee on Climate Change.

CIBSE. 2013. *CIBSE TM52:2013 – The limits of thermal comfort: avoiding overheating in European buildings*. The Chartered Institution of Building Services Engineers.

CIBSE. 2015. *CIBSE Guide A – Environmental design*. The Chartered Institution of Building Services Engineers.

Coley, D., Kershaw, T., and Eames, M. 2012. A comparison of structural and behavioural adaptations to future proofing buildings against higher temperatures. *Building and Environment* 55. Implications of a Changing Climate for Buildings, pp. 159 – 166. DOI: 10.1016/j.buildenv.2011.12.011.

DBIS. 2010. *Low carbon construction innovation & growth team: final report*. UK Department for Business, Innovation & Skills.

DCLG. 2015a. *English housing survey: HOUSEHOLDS 2013–14*. UK Government department for communities and local government.

DCLG. 2015b. *English housing survey: Headline report 2013 to 2014*. UK Government department for communities and local government.

Dengel, A. and Swainson, M. 2012. *Overheating in new homes: A review of the evidence*. NHBC Foundation.

Derbez, M., Berthineau, B., Cochet, V., Pignon, C., Ribéron, J., Wyart, G., Mandin, C., and Kirchner, S. 2014. A 3-year follow-up of indoor air quality and comfort in two energy-efficient houses. *Building and Environment* 82, pp. 288 – 299. DOI: 10.1016/j.buildenv.2014.08.028.

EN. 2007. *EN 15251:2007 – Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics*. European Standard.

Fabi, V., Andersen, R. V., Corgnati, S., and Olesen, B. W. 2012. Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and models. *Building and Environment* 58, pp. 188–198. DOI: 10.1016/j.buildenv.2012.07.009.

Firth, S. and Wright, A. 2008. Investigating the thermal characteristics of English dwellings: Summer temperatures.

Gabriel, K. M. A. and Endlicher, W. R. 2011. Urban and rural mortality rates during heat waves in Berlin and Brandenburg, Germany. *Environmental Pollution* 159 (8-9), pp. 2044 – 2050. DOI: 10.1016/j.envpol.2011.01.016.

Hamilton, I. G., Shipworth, D., Summerfield, A. J., Steadman, P., Oreszczyn, T., and Lowe, R. 2014. Uptake of energy efficiency interventions in English dwellings. *Building Research and Information* 42 (3), pp. 255 – 275. DOI: 10.1080/09613218.2014.867643.

Hondula, D. M., Davis, R. E., Leisten, M. J., Saha, M. V., Veazey, L. M., and Wegner, C. R. 2012. Fine-scale spatial variability of heat-related mortality in Philadelphia County, USA, from 1983-2008: A case-series analysis. *Environmental Health: A Global Access Science Source* 11 (1). DOI: 10.1186/1476-069X-11-16.

Hoof, J. van, Kort, H. S. M., Hensen, J. L. M., Duijnstee, M. S. H., and Rutten, P. G. S. 2010. Thermal comfort and the integrated design of homes for older people with dementia. *Building and Environment* 45 (2). 1st International Symposium on Sustainable Healthy Buildings, pp. 358 – 370. DOI: 10.1016/j.buildenv.2009.06.013.

ISO. 2005. *ISO 7730:2005 – Ergonomics of the thermal environment: Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria*. International Organization for Standardization.

Ji, Y., Fitton, R., Swan, W., and Webster, P. 2014. Assessing overheating of the UK existing dwellings – A case study of replica Victorian end terrace house. *Building and Environment* 77, pp. 1 – 11. DOI: 10.1016/j.buildenv.2014.03.012.

Johnson, H., Kovats, R. S., McGregor, G., Stedman, J., Gibbs, M., Walton, H., Cook, L., and Black, E. 2005. The impact of the 2003 heat wave on mortality and hospital admissions in England. *Health statistics quarterly / Office for National Statistics* (25), pp. 6 – 11.

Jones, G. S., Stott, P. A., and Christidis, N. 2008. Human contribution to rapidly increasing frequency of very warm Northern Hemisphere summers. *Journal of Geophysical Research Atmospheres* 113 (2). DOI: 10.1029/2007JD008914.

Kottek, M., Grieser, J., Beck, C., Rudolf, B., and Rubel, F. 2006. World map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift* 15 (3), pp. 259 – 263. DOI: 10.1127/0941-2948/2006/0130.

Laaidi, K., Zeghnoun, A., Dousset, B., Bretin, P., Vandentorren, S., Giraudet, E., and Beaudeau, P. 2012. The impact of heat islands on mortality in Paris during the August 2003 heat wave. *Environmental Health Perspectives* 120 (2), pp. 254 – 259. DOI: 10.1289/ehp.1103532.

Lomas, K. J. and Kane, T. 2013. Summertime temperatures and thermal comfort in UK homes. *Building Research & Information* 41 (3), pp. 259–280. DOI: 10.1080/09613218.2013.757886.

Mavrogianni, A., Wilkinson, P., Davies, M., Biddulph, P., and Oikonomou, E. 2012. Building characteristics as determinants of propensity to high indoor summer temperatures in

London dwellings. *Building and Environment* 55. Implications of a Changing Climate for Buildings, pp. 117 – 130. DOI: 10.1016/j.buildenv.2011.12.003.

McLeod, R. S., Hopfe, C. J., and Kwan, A. 2013. An investigation into future performance and overheating risks in Passivhaus dwellings. *Building and Environment* 70, pp. 189 – 209. DOI: 10.1016/j.buildenv.2013.08.024.

McManus, A., Gaterell, M. R., and Coates, L. E. 2010. The potential of the Code for Sustainable Homes to deliver genuine 'sustainable energy' in the UK social housing sector. *Energy Policy* 38 (4), pp. 2013 – 2019. DOI: 10.1016/j.enpol.2009.12.002.

Meehl, G. A. and Tebaldi, C. 2004. More intense, more frequent, and longer lasting heat waves in the 21st century. *Science* 305 (5686), pp. 994 – 997. DOI: 10.1126/science.1098704.

Mickaël, D., Bruno, B., Valérie, C., Murielle, L., Cécile, P., Jacques, R., and Severine, K. 2014. Indoor air quality and comfort in seven newly built, energy-efficient houses in France. *Building and Environment* 72, pp. 173 – 187. DOI: 10.1016/j.buildenv.2013.10.017.

Murphy, J., Sexton, D., Jenkins, G., Boorman, P., Booth, B., Brown, K., Clark, R., Collins, M., Harris, G., and Kendon, L. 2009. *UK Climate Projections science report: Climate change projections*. Met Office Hadley Centre.

Nicol, F. and Humphreys, M. 2007. Maximum temperatures in European office buildings to avoid heat discomfort. *Solar Energy* 81 (3), pp. 295 – 304. DOI: 10.1016/j.solener.2006.07.007.

Nicol, F. and Humphreys, M. 2010. Derivation of the adaptive equations for thermal comfort in free-running buildings in European standard EN15251. *Building and Environment* 45 (1). International Symposium on the Interaction between Human and Building Environment Special Issue Section, pp. 11 – 17. DOI: 10.1016/j.buildenv.2008.12.013.

ONS. 2011. *Census data 2011: Household reference person aged 65 and over in England and Wales*. Office for National Statistics.

Oikonomou, E., Davies, M., Mavrogianni, A., Biddulph, P., Wilkinson, P., and Kolokotroni, M. 2012. Modelling the relative importance of the urban heat island and the thermal quality of dwellings for overheating in London. *Building and Environment* 57, pp. 223 – 238. DOI: 10.1016/j.buildenv.2012.04.002.

Peacock, A. D., Jenkins, D. P., and Kane, D. 2010. Investigating the potential of overheating in UK dwellings as a consequence of extant climate change. *Energy Policy* 38 (7). Large-scale wind power in electricity markets with Regular Papers, pp. 3277 – 3288. DOI: 10.1016/j.enpol.2010.01.021.

Porritt, S. M., Cropper, P. C., Shao, L., and Goodier, C. I. 2012. Ranking of interventions to reduce dwelling overheating during heat waves. *Energy and Buildings* 55. Cool Roofs, Cool Pavements, Cool Cities, and Cool World, pp. 16 – 27. DOI: 10.1016/j.enbuild.2012.01.043.

Porritt, S., Shao, L., Cropper, P., and Goodier, C. 2011. Adapting dwellings for heat waves. *Sustainable Cities and Society* 1 (2), pp. 81 – 90. DOI: 10.1016/j.scs.2011.02.004.

Robine, J.-M., Cheung, S. L. K., Le Roy, S., Van Oyen, H., Griffiths, C., Michel, J.-P., and Herrmann, F. R. 2008. Death toll exceeded 70,000 in Europe during the summer of 2003. *Comptes Rendus – Biologies* 331 (2), pp. 171 – 178. DOI: 10.1016/j.crvi.2007.12.001.

Roetzel, A., Tsangrassoulis, A., Dietrich, U., and Busching, S. 2010. A review of occupant control on natural ventilation. *Renewable and Sustainable Energy Reviews* 14 (3), pp. 1001 – 1013. DOI: 10.1016/j.rser.2009.11.005.

Rohdin, P., Molin, A., and Moshfegh, B. 2014. Experiences from nine passive houses in Sweden – Indoor thermal environment and energy use. *Building and Environment* 71, pp. 176 – 185. DOI: 10.1016/j.buildenv.2013.09.017.

Sakka, A., Santamouris, M., Livada, I., Nicol, F., and Wilson, M. 2012. On the thermal performance of low income housing during heat waves. *Energy and Buildings* 49, pp. 69 – 77. DOI: 10.1016/j.enbuild.2012.01.023.

Smargiassi, A., Goldberg, M. S., Plante, C., Fournier, M., Baudouin, Y., and Kosatsky, T. 2009. Variation of daily warm season mortality as a function of micro-urban heat islands. *Journal of Epidemiology and Community Health* 63 (8), pp. 659 – 664. DOI: 10.1136/jech.2008.078147.

Stocker, T. F. et al. 2013. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Intergovernmental Panel on Climate Change (IPCC). DOI: 10.1017/CBO9781107415324.

Tabatabaei Sameni, S. M., Gaterell, M., Montazami, A., and Ahmed, A. 2015. Overheating investigation in UK social housing flats built to the Passivhaus standard. *Building and Environment* 92, pp. 222 – 235. DOI: 10.1016/j.buildenv.2015.03.030.

Tillson, A.-A., Oreszczyn, T., and Palmer, J. 2013. Assessing impacts of summertime overheating: some adaptation strategies. *Building Research & Information* 41 (6), pp. 652 – 661. DOI: 10.1080/09613218.2013.808864.

Tweed, C., Humes, N., and Zapata-Lancaster, G. 2015. The changing landscape of thermal experience and warmth in older people's dwellings. *Energy Policy* 84, pp. 223 – 232. DOI: 10.1016/j.enpol.2015.03.011.

Vardoulakis, S., Dimitroulopoulou, C., Thornes, J., Lai, K.-M., Taylor, J., Myers, I., Heaviside, C., Mavrogianni, A., Shrubsole, C., Chalabi, Z., Davies, M., and Wilkinson, P. 2015. Impact of climate change on the domestic indoor environment and associated health risks in the UK. *Environment International* 85, pp. 299 – 313. DOI: 10.1016/j.envint.2015.09.010.

Wells, E. M., Berges, M., Metcalf, M., Kinsella, A., Foreman, K., Dearborn, D. G., and Greenberg, S. 2015. Indoor air quality and occupant comfort in homes with deep versus conventional energy efficiency renovations. *Building and Environment* 93, pp. 331 – 338. DOI: 10.1016/j.buildenv.2015.06.021.

White-Newsome, J. L., Sánchez, B. N., Jolliet, O., Zhang, Z., Parker, E. A., Dvonch, J. T., and O'Neill, M. S. 2012. Climate change and health: Indoor heat exposure in vulnerable populations. *Environmental Research* 112, pp. 20 – 27. DOI: 10.1016/j.envres.2011.10.008.

Willand, N., Ridley, I., and Pears, A. 2016. Relationship of thermal performance rating, summer indoor temperatures and cooling energy use in 107 homes in Melbourne, Australia. *Energy and Buildings* 113, pp. 159 – 168. DOI: 10.1016/j.enbuild.2015.12.032.

Wright, A. J., Young, A. N., and Natarajan, S. 2005. Dwelling temperatures and comfort during the August 2003 heat wave. *Building Services Engineering Research and Technology* 26 (4), pp. 285–300. DOI: 10.1191/0143624405bt136oa.

Yu, C. W. F. and Kim, J. T. 2012. Low-Carbon Housings and Indoor Air Quality. *Indoor and Built Environment* 21 (1), pp. 5–15. DOI: 10.1177/1420326X11431907.

Postscript

In this Chapter the analyses done on the collected thermal comfort data use simple logistic regression. The reason why this study has used this statistical technique is double: on one side the previous Chapter has already shown the difficulties in modelling thermal comfort using both linear regression and the Griffiths method, on the other side researchers had previously used logistic regression when modelling the European SCATs data (from which the European adaptive model is derived) so its use allowed to directly compare the results with the European adaptive model.

In the following Chapter these concepts are further explored and the use of different types of logistic regressions (simple, multinomial and ordinal) in adaptive thermal comfort research is reviewed. Also, their predictive power in modelling the ASHRAE RP-884 dataset is tested against that of new statistical techniques (decision tree and random forest).

Chapter 4

The influence of relative humidity on adaptive thermal comfort

Abstract

Buildings generate nearly 30% of global carbon emissions, primarily due to the need to heat or cool them to meet acceptable indoor temperatures. In the last 20 years, the empirically derived adaptive model of thermal comfort has emerged as a powerful alternative to fixed set-point driven design. However, current adaptive standards offer a simple linear relationship between the outdoor temperature and the indoor comfort temperature, assumed to sufficiently explain the effect of all other variables, e.g. relative humidity (*RH*) and air velocity. The lack of a signal for *RH* is particularly surprising given its well-known impact on comfort. Attempts in the literature to either explain the lack of such a signal or demonstrate its existence, remain scattered, unsubstantiated and localised. In this paper we demonstrate, for the first time, that a humidity signal exists in adaptive thermal comfort using global data to form two separate lines of evidence: a meta-analysis of summary data from 63 field studies and detailed field data from 39 naturally ventilated buildings over 8 climate types. We implicate *method selection* in previous work as the likely cause of failure to detect this signal, by demonstrating that our chosen method has a 56% lower error rate. We derive a new designer-friendly *RH*-inclusive adaptive model that significantly extends the range of acceptable indoor conditions for designing low-energy naturally-conditioned buildings all over the world. This is demonstrated through parametric simulations in 13 global locations, which reveal that the current model overestimates overheating by 30% compared to the new one.

Preamble

This chapter addresses **R**esearch **Q**uestion **3** and aims at understanding the influence of relative humidity on adaptive thermal comfort. The research is carried out by using the freely available ASHRAE RP-884 dataset along with new global data acquired by reviewing thermal comfort field studies reported in the literature. As the used data are global (and not just collected in Europe), the ASHRAE adaptive model is here used as reference and for direct comparison.

Chronologically, this represents one of the last published work of this thesis but it has indeed been thought and developed during the entire course of this PhD. It answers some of the questions arisen while processing and analysing the data collected in the field studies described and reported in Chapter 2 and Chapter 3. Particular focus is given to showing the limitations of the Griffiths method which is the most commonly used method in adaptive thermal comfort research. Furthermore, the statistical methods which are used to model thermal comfort (including the logistic regression technique employed in the previous Chapter) are reviewed and, using global data, the predictive capability of these methods is compared to that of new ones (decision trees and random forest). In particular, the high prediction power of machine learning techniques is highlighted.

This chapter is totally based on a same-titled paper published in Building and Environment in 2017, more details are provided in the next section.

Declaration of Authorship

This declaration concerns the article entitled: The influence of relative humidity on adaptive thermal comfort	
Status	Published in Building and Environment.
Details	**Marika Vellei**, Manuel Herrera, Daniel Fosas & Sukumar Natarajan, The influence of relative humidity on adaptive thermal comfort, Building and Environment, 2017, Volume 124, Pages 171-185. DOI: doi.org/10.1016/j.buildenv.2017.08.005
Authors' contribution	The author of this thesis has primarily (80%) contributed to defining the methodology adopted in this work and to writing the manuscript. The dynamic thermal simulations have been entirely (100%) performed by D. Fosas with EnergyPlus (v8.7). While the statistical analyses have been entirely (100%) carried out by the author of this thesis with the programming language Python. Each author's exact contributions to the article is outlined below: **M. Vellei**: Formulation of ideas (80%), Design of methodology (80%), Processing/Analysis of data (100%), Preparation of the manuscript (80%). D. Fosas: Dynamic thermal simulations (100%). M. Herrera: Formulation of ideas (10%), Design of methodology (10%). S. Natarajan: Formulation of ideas (10%), Design of methodology (10%), Editing drafts of manuscript (20%).
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.
Date and Signature	

4.1 Introduction

According to the ANSI/ASHRAE Standard 55-2013, thermal comfort is "that condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation" (ASHRAE, 2013). Indoor thermal comfort is among the most important factors affecting occupant well-being, health and productivity in buildings (Frontczak and Wargocki, 2011). This is important since people spend up to 90% of their time inside buildings, especially in developed countries (Klepeis et al., 2001). However, typical buildings impose a substantive energy cost to heat or cool them to the desired comfort level. In developed countries, with largely saturated demand, this is estimated to be 20 – 40% of the total final energy use and nearly 30% of all CO_2 emissions (Pérez-Lombard et al., 2008; Nejat et al., 2015). This makes the building sector the single largest contributor to global CO_2 production and hence climate change. Thermal comfort standards are therefore central to not merely providing comfortable environments but also ensuring a sustainable design through low heating and cooling energy use in buildings.

Two types of comfort standards currently prevail in the literature: *steady-state* and *adaptive*. The steady-state model, pioneered by P.O. Fanger in the late 1960s, is a heat-balance model that defines combinations of a set of six indoor environmental variables that will provide acceptable thermal conditions to the majority of occupants (Fanger, 1970). The six variables are: air temperature, mean radiant temperature, air movement, air humidity, clothing insulation and metabolic heat generated by human activity. These are folded into an empirical relationship to provide a Predicted Mean Vote (PMV) of thermal comfort, underpinned by the idea of a *neutral temperature* for a given value of the other parameters. In contrast, the relatively recent development of the ASHRAE adaptive model (ASHRAE, 2013) and its European counterpart (EN, 2007) are based on the idea that the range of acceptable temperatures in naturally ventilated (NV) buildings is larger than in air-conditioned (AC) buildings and dependent purely on the prevailing external temperature. Using large scale survey data, such as the ASHRAE RP-884 database (De Dear et al., 1998; Dear and Brager, 2002), from different climatic zones around the world, these models derive a simple linear relationship between the indoor comfort temperature and the outdoor temperature.

According to Nicol and Humphreys (2002), the reason for this extreme simplification is that some of Fanger's conventional thermal comfort factors, i.e. clothing insulation and metabolic rate, are significantly correlated to the outdoor air temperature. Interestingly, although relative humidity and air velocity are not shown to strongly depend on the outdoor air temperature (Halawa and Hoof, 2012), their effect is not seen to be large enough to warrant inclusion in the model (Nicol, 2004). However, their importance in determining physiological thermal comfort is well documented (Parsons, 2002). It is known, for example, that high indoor humidity impairs sweat-induced evaporative cooling, which is the principal physiological mechanism by which the body rejects heat, particularly in warm environments (Andersen et al., 1973; Jing et al., 2013; Zhang et al., 2014; Song et al., 2015; Jin et al., 2017). Air movement also influences the evaporative and convective heat exchange to and from the body, affecting its temperature (Cândido et al., 2010).

The absence of a signal for relative humidity (*RH*) is surprising since outdoor humidity is likely to have a bigger effect on indoor humidity than parameters such as occupant density (which increases indoor moisture production) or window operation (which could decrease indoor humidity if external humidity is lower). This is supported by Figure 4.1, which shows that the Pearson correlation coefficient between mean daily indoor (*RH*) and outdoor (RH_{out}) relative humidity in the ASHRAE RP-884 database is significantly higher in naturally ventilated (0.52) than in air-conditioned (0.33) buildings. Hence, one might expect that the comfort response in NV buildings is significantly mediated by the internal relative humidity, which in turn is a function of the external humidity.

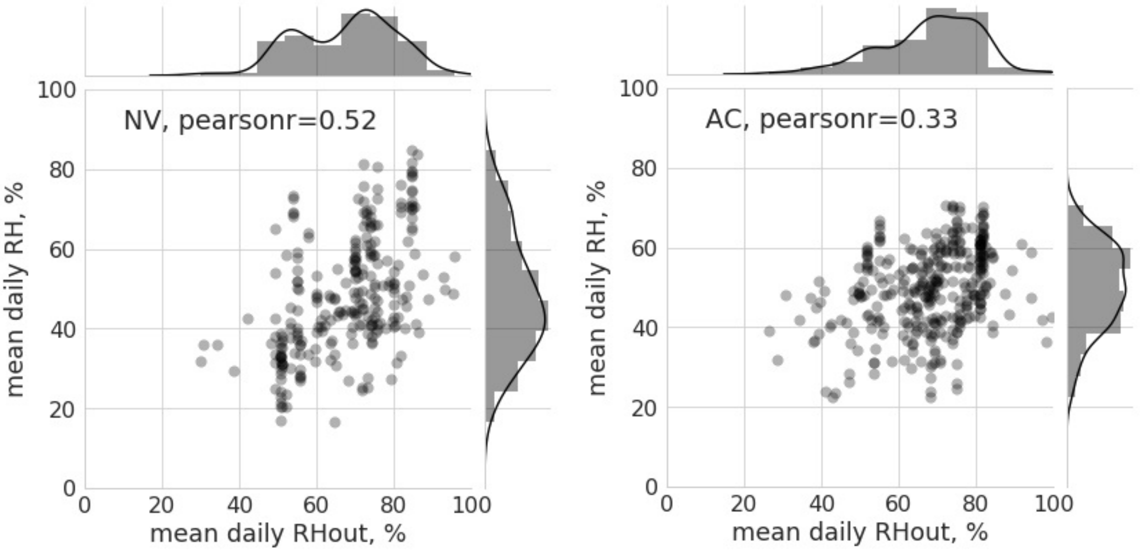


Figure 4.1: Scatterplot and histograms with kernel density estimates (derived using a Gaussian characteristic function) of mean daily indoor (*RH*) and outdoor (RH_{out}) relative humidity for the ASHRAE RP-884 naturally ventilated (NV, left) and air-conditioned (AC, right) buildings. The number *pearsonr* is the Pearson correlation coefficient.

External and internal air velocities, on the other hand, are likely to be decoupled since occupant control of ventilation through window operation and use of fans is likely to have at least as great an influence on the indoor air velocity as the prevailing outdoor weather conditions. Since increased occupant control is now well established as a critical component in increasing occupant satisfaction (Boerstra et al., 2013), the absence of an air velocity signal could therefore be hypothesised to be due to the studied buildings having good occupant control of windows and fans (De Dear et al., 1998). However, unlike *RH*, the absence of recorded external wind data in the ASHRAE RP-884 database precludes a test of this hypothesis.

The lack of a clear humidity signal, upon which to differentiate adaptive indoor comfort in the present models, is therefore puzzling, and the subject of much previous work in the field (Nicol, 2004; Givoni et al., 2006; Toe and Kubota, 2013; Nguyen et al., 2012). However, no clear explanation for the lack of a humidity signal or a convincing formulation of the effect of humidity on adaptive thermal comfort has hereto emerged.

To address this, we begin by examining the effect of *RH* on occupant thermal sensitivity through an analysis of the regression gradient in Section 4.2. This analysis provides the first clear evidence that *RH* has a measurable impact on occupant thermal sensation. A second independent line of evidence emerges from the analysis in Section 4.3, which compares the ability of a range of statistical methods already used in the literature against new candidate methods, to explain the data contained in ASHRAE RP-884 database. Although both methods independently verify our hypothesis that *RH* has an important role to play in adaptive thermal comfort, neither is capable of a practical formulation that can be used by practitioners. Hence, using the knowledge gained in Sections 4.2 and 4.3, we cast the RP-884 data within a new formulation, but one that has the strength of being familiar to practitioners. This provides a *new* adaptive comfort model selectable by different classes of humidity (Section 4.4). Finally, Section 4.5 demonstrates the use of the new model in building performance assessment across a range of global climates.

4.2 The effect of relative humidity on thermal sensitivity

The current adaptive thermal comfort models are derived using a simple linear regression of neutral temperatures against the corresponding mean outdoor air temperatures, acquired through field studies. The neutral temperature is defined as the indoor temperature which an average occupant finds neither warm nor cool, hence neutral (Mishra and Ramgopal, 2013). This has historically been determined using two methods:

- By regressing the Thermal Sensation Vote (TSV) against the indoor temperature, with the neutral temperature corresponding to a $TSV = 0$ (Humphreys et al., 2013). Three different types of linear regression are used in the literature: *simple*, *binned* (i.e. binning the TSV in 0.5°C or 1°C intervals) and *weighted binned*, where the weights are the number of votes in each interval. The gradient of the linear regression fitted between the TSV and the indoor temperature indicates the temperature perturbation needed for a change of 1 unit in TSV. It is therefore a measure of occupant sensitivity to indoor temperature changes and gives the degree to which a population can adapt to variations in the thermal environment. Lower gradients can be associated with more effectively adapted and less sensitive occupants (Dear et al., 2015). A lower slope is also indicative of a larger comfort band which means that occupants can tolerate exposure to a wider range of indoor temperatures (Nguyen et al., 2012; Humphreys et al., 2013; Indraganti, 2010b).
- By using the *Griffiths method*. Here, the neutral temperature T_n is derived through the following equation:

$$T_n = T_m - TSV_m/G \tag{4.1}$$

  where TSV_m is the mean Thermal Sensation Vote, T_m is the mean indoor temperature in °C and G is the assumed regression gradient, also called *Griffiths coefficient*, in /°C. This method has been used in many field studies all over the world to derive neutral temperatures (Mustapa et al., 2016; Thapa et al., 2016; Damiati et al., 2016; Yang et al., 2017; Liu et al., 2017; Liu et al., 2013; Mishra and Ramgopal, 2015b,b; Olweny et al., 2016), including the derivation of the European adaptive thermal comfort model (Nicol and Humphreys, 2010). This method has been deemed useful when it is difficult to reach statistically significant linear regressions, due to, for example, small sample sizes, low variance of the indoor temperature, or non-linearly dependent data with interaction effects.

Griffiths proposed a gradient equal to 0.33 to use when deriving adaptive models (Griffiths, 1991), based on Fanger's regression slope (Fanger, 1970). However, there is considerable variation in the actual values of G used in the literature, ranging from 0.25 to 0.50 (Humphreys et al., 2013; Mustapa et al., 2016; Damiati et al., 2016; Nicol et al., 1994; Rijal, 2014). The reasons for this vary, but are driven by the need for G to be *fit to purpose*. Examples include: G = 0.50 to improve the coefficient of determination R^2 of the European adaptive equation (Nicol and Humphreys, 2010); and G = 0.38 derived from the weighted mean value of all the regression gradients included in Nguyen's database of field studies in South-East Asia, thus localising its use to hot-humid climates (Nguyen et al., 2012).

Nguyen et al. (2012) showed that adaptive equations are very sensitive to changes in Griffiths constants (Figure 4.2), thus suggesting that the choice of the right regression gradient is crucial when deriving an adaptive model.

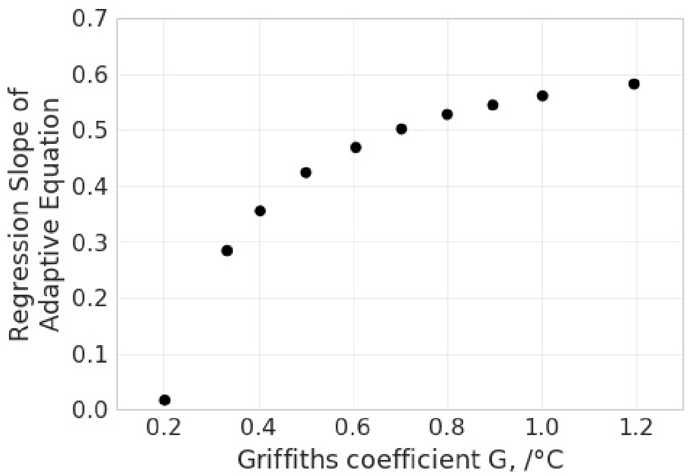


Figure 4.2: The relationship between the regression slope of the adaptive comfort equation and the value given to the Griffiths coefficient G. Adapted from: Nguyen et al. (2012).

To put this in context, we reviewed earlier work on the regression gradient and found that:

- The regression gradient decreases as the standard deviation of the indoor temperature ($\sigma(T_i)$) increases, possibly indicating that larger standard deviations of the indoor temperature allow greater opportunities for behavioural and psychological adaptation (Dear et al., 2015; Humphreys et al., 2007).
- Naturally ventilated buildings have lower gradients than air-conditioned buildings, again indicating greater adaptive opportunities in the former (De Dear et al., 1998; Manu et al., 2016; Yang and Zhang, 2008; Luo et al., 2015).

- Occupants are more thermally sensitive to indoor temperature variations during seasonal extremes (i.e. summer and winter) than in the intervening milder seasons (Song et al., 2015; Liu et al., 2017; Dhaka et al., 2013).
- Higher humidity leads to higher gradients and hence to greater occupant sensitivity to temperature variations (Indraganti et al., 2013b).
- Higher air speed results in lower gradients in warm climates (Givoni et al., 2006).
- Gradients in homes can be significantly lower than those found in offices, again likely due to the larger adaptive opportunities in terms of clothing and air speed adjustments available (De Dear et al., 1998; Ye et al., 2006; Rijal et al., 2010).

While several variables are seen to affect the regression gradient and hence thermal adaptation, the evidence is scattered or localised. For example, only one paper has shown the effect of humidity on the gradient and only based on data from two cities in India (Indraganti et al., 2013b).

Hence, we examine this further through a meta-analysis of field studies in *naturally-conditioned* buildings. Buildings that are either naturally ventilated or mixed-mode (but operating in free-running mode during the field study) are defined as naturally-conditioned. A total of 63 field studies were thus selected, 18 of which come from the standardised ASHRAE RP-884 database (De Dear et al., 1998; Dear and Brager, 2002; ASHRAE, 2013), with the remaining 45 studies from 24 papers published after the release of ASHRAE RP-884. Studies from the ASHRAE RP-884 database were filtered by selecting those achieving statistical significance ($p < 0.05$) when linearly regressing TSV against the operative temperature in each study. A majority of the studies are in residential and office buildings, although other building types (educational, museum and cathedral) are present. We include all these building types in the meta-analysis without distinction. This approach is consistent with the ASHRAE standard, which is deemed applicable to all building types. A summary of the selected studies is given in the Appendix.

Our meta-analysis takes the form of a multiple regression model derived from the summary statistics of the 63 selected thermal comfort field studies. The response or dependent variable in this model is the regression gradient a and the predictor variables are one or more of the available variables from the selected studies, which were:

- Indoor temperature (T_i, °C) variously measured as:
  - Dry bulb temperature (T_{db}, °C),
  - Globe temperature (T_g, °C), measured at the centre of a blackened globe with standard diameter of 0.15 m,
  - Operative temperature (T_{op}, °C), defined as the weighted mean of the air and mean radiant temperatures but frequently simplified as the arithmetic mean, an approximation that works well when the difference between the air and mean radiant temperatures is small.
- Mean daily outdoor air temperature on the days of the survey (T_{out}, °C),
- Relative humidity (RH, %),

- Total insulation ($INSUL$, clo),
- Air velocity (VA, m/s),
- Metabolic rate of the subject (MET, met),
- Gender of the subject (SEX, 0=male/1=female).

Here, the indoor variables can be classed into two categories:

- *CLASS I*: Binding environmental variables over which occupants have little control: indoor temperature (T_i) and humidity (RH).
- *CLASS II*: Partially or wholly occupant-mediated variables: air velocity (VA), clothing insulation ($INSUL$) and metabolic rate (MET).

Three observations are pertinent to the selection and use of these variables in our meta-analysis:

- Summary data for *CLASS II* variables were not always available whereas data for *CLASS I* variables were available for all studies. Given that *CLASS II* variables, unlike those of *CLASS I*, can be directly controlled by the occupants of naturally-conditioned buildings, and can hence not be viewed as pure predictors, we only consider *CLASS I* variables in our model.
- The reviewed field studies use different metrics for the indoor temperature, i.e. dry-bulb air temperature, globe temperature and operative temperature. In our model, we refer to them under the general term indoor temperature (T_i) since several studies have shown that differences between radiant and air temperatures in indoor environments are usually very limited (Nicol et al., 2012), with exceptions in indoor spaces with high thermal mass. Since there are no buildings classed as high mass constructions in our sample, this is not a significant risk.
- Three different methods of linear regression are used in the selected studies: simple, binned and weighted binned. We treat these equally since Djamila et al. (2013) has shown that the regression gradients calculated using either methods are very similar. Details of the metrics and methods used in each field study can be found in Appendix.

Hence, the selected predictor variables for our model are the mean and standard deviation of indoor temperature and relative humidity, i.e. $\mu(T_i)$, $\mu(RH)$, $\sigma(T_i)$ and $\sigma(RH)$, computed over the total length of each study period. Mean and standard deviation of indoor temperature and relative humidity for all the selected studies are shown in Figure 4.3. Relative humidity ranges from 24% to 76%, while the temperature spans from 19°C to 35°C; providing a large spread of available mean environmental conditions. There is a large variation in the standard deviations of T_i (1°C to 9°C) and RH (3% to 23%) due to the inclusion of field studies from all seasons (see also Appendix).

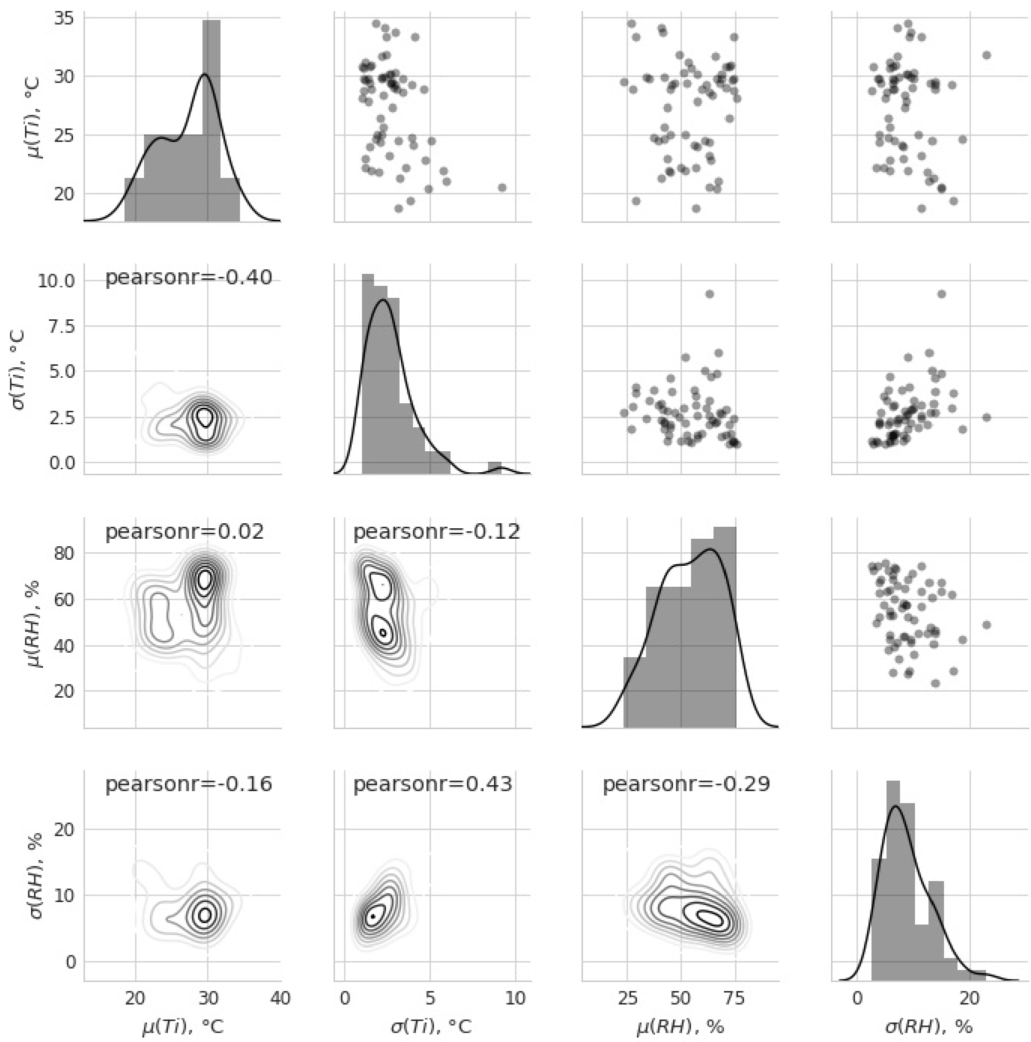


Figure 4.3: Scatterplot matrix with histograms and kernel density estimates (derived using a Gaussian characteristic function) in diagonal, two-dimensional kernel density plots in the lower half and bivariate scatterplots in the upper half. The number *pearsonr* is the Pearson correlation coefficient.

4.2.1 New insights on the regression gradient

We first use non-linear least squares to fit an exponential function to the indoor temperature data. The resulting function is equal to $e^{-0.8\sigma(T_i)}$. Then, a multiple linear regression technique is used to model the effect of $\mu(T_i)$, $\mu(RH)$, $e^{-0.8\sigma(T_i)}$ and $\sigma(RH)$ on the regression gradient. All the predictors are regressed collectively against the dependent variable. Then, each predictor is removed from the model to observe the effect on the coefficient of determination (R^2), in a backward elimination process. R^2 measures the proportion of variability in the variable response that can be explained using the predictor variables, and will always fall in the interval [0, 1]. The closer R^2 is to 1, the larger the proportion of the variability in the response variable explained by the regression and the better the model. If the removal of a given variable does not significantly reduce R^2 ($p < 0.05$), then it is eliminated from the model. This process resulted in the rejection of $\mu(T_i)$ and $\sigma(RH)$. Hence, our model suggests that the regression gradient is dependent on $\mu(RH)$ and $e^{-0.8\sigma(T_i)}$ but independent of $\mu(T_i)$ and $\sigma(RH)$:

$$a = 0.0030\mu(RH) + 0.7475e^{-0.8\sigma(T_i)} \tag{4.2}$$

With $N = 63$ and $R^2 = 0.48$.

Table 4.1: Results of the multiple linear regression model for the regression gradient.

	coef.	SE	p-value	[95.0% conf. int.]
Intercept	-0.0349	0.062	0.578	-0.160 to 0.090
$\mu(RH)$	0.7475	0.127	0.000	0.494 to 1.001
$e^{-0.8\sigma(T_i)}$	0.0030	0.001	0.014	0.001 to 0.005

Humphreys observes that the gradient peaks at a $\sigma(T_i) = 1$ and decreases at lower values of the standard deviation, possibly due to errors in the measurements and in the equation of the operative temperature (Humphreys et al., 2007). In contrast, our model suggests that the regression gradient exponentially increases at decreasing standard deviation. Significantly, a Griffiths coefficient equal to 0.50 – used to derive the European adaptive equation (Nicol and Humphreys, 2010) – occurs in only 8% of the sample data.

Additionally, for the first time we observe that the gradient increases at increasing levels of RH (Figure 4.4). Since the acceptable operative temperature range is inversely proportional to the regression gradient, this also means that the band of acceptable temperature reduces as the RH increases.

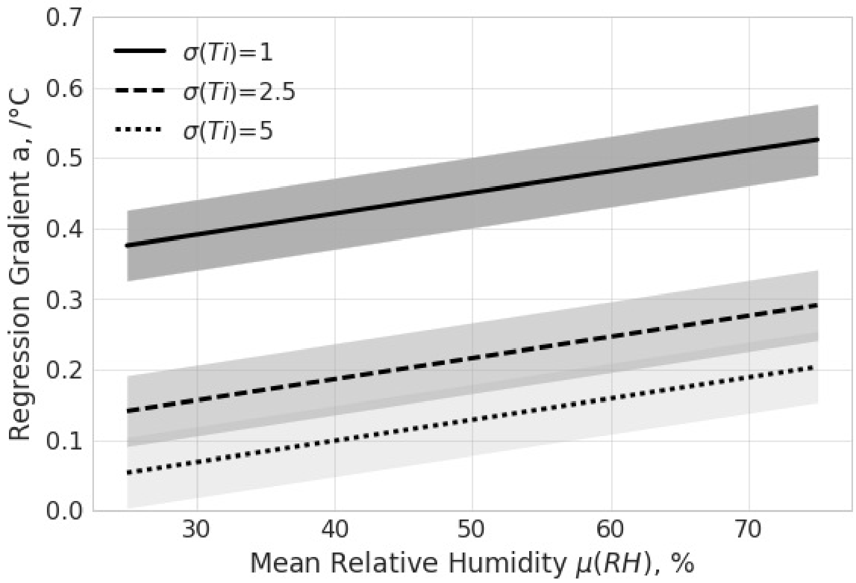


Figure 4.4: Regression gradient a as a function of the mean relative humidity $\mu(RH)$ for three different values of $\sigma(T_i)$; fitted model with 95% confidence bands.

Our analysis above has provided the clearest evidence thus far for the existence of a humidity signal in adaptive thermal comfort. However, this raises the question of why such a signal was not evident when the adaptive model was being created. After all, if the signal existed it must have been present in the ASHRAE RP-884 data itself, given its detail and geographical spread. One obvious reason is that the adaptive model is derived by regressing the neutral temperature in each location against the corresponding mean outdoor temperature. This process ignores the effect of the gradient, since the neutral temperature is just one point on the gradient line. A subtler reason is to do with the method: perhaps the choice of simple linear regression as a means of analysis did not provide the fidelity needed to demonstrate the presence of a humidity signal. The next section illustrates this by using *a first principles approach*, i.e. bringing to bear new statistical techniques that were uncommon when the adaptive model was first proposed.

4.3 A first principles approach

In the preceding section we were able to demonstrate the presence of a humidity signal in adaptive thermal comfort by undertaking a meta-analysis of descriptive statistics from a range of studies. In this section, we take a first principles approach by analysing data from the only publicly available data set that provides complete raw data for a wide range of geographically dispersed NV buildings: the ASHRAE RP-884 data set. Our working hypothesis is that these data will, in principle, be adequate to extract the *RH* signal (if it exists) provided a method of sufficient power is used.

4.3.1 Discussion of methods

A review of the literature suggests that simple and multiple *linear regressions* are the most widely used methods for modelling occupant thermal sensation in thermal comfort research (Mishra and Ramgopal, 2013). Simple and weighted linear regressions have been extensively used for calculating occupant neutral temperatures (De Dear et al., 1998; Nicol and Humphreys, 2002; Mustapa et al., 2016; Yang and Zhang, 2008; Indraganti et al., 2013b; Luo et al., 2014; Farghal and Wagner, 2010; Gómez-Azpeitia et al., 2012; Indraganti, 2010a; Ogbonna and Harris, 2008; Moujalled et al., 2008; Dhaka et al., 2015; Karyono, 2008); and starting with Bedford's first attempt in the 1930s (Nicol et al., 2012), multiple linear regression has also been largely used to study the impact of different environmental variables on occupant thermal comfort responses (Sharma and Ali, 1986; Givoni et al., 2006; Rijal, 2014; Indraganti et al., 2013b; Djamila et al., 2013; Pellegrino et al., 2012; Rangsiraksa, 2006; Erlandson et al., 2003). However, if we want to directly model the categorical variable TSV, a model that provides continuous estimates guarantees neither good performance nor proper validation of the linearity hypothesis. Hence, we consider five other methods that either directly improve linear regression or bring new analytical capabilities, described below.

Logistic regression Logistic regression is a regression specifically designed for binary or dichotomous dependent variables (Hilbe, 2009). The logarithm of the odds ratio, i.e. $\ln(P(Y)/(1-P(Y))$, of the variable of interest (Y) is modelled based on a combination of values taken by the predictor variables.

Logistic regression can handle all sorts of relationships since it applies a non-linear log transformation to the predicted odds ratio. Therefore, the key assumptions of linear regression and, in general, of linear models (i.e. normality, homoscedasticity and independence of the model residuals) do not need to be met. However, problems could still arise if multicollinearity exists (i.e. when two or more predictor variables are highly correlated). Issues in such a model include significant variability in the model coefficients, reducing its utility, or the suggestion of unrealistic relationships between the dependent variable and its predictors. Nonetheless, the thermal comfort literature has recognized logistic regression as a suitable alternative to simple linear regression to deal with discrete dependent variables (Webb, 1959; Indraganti et al., 2015). When more than one independent variable is hypothesised to affect the dependent variable, multiple logistic regression is used, such as its application in the wider field of indoor environmental quality research (Wong et al., 2008; Lai et al., 2009).

Multinomial logistic regression When the dependent variable can take a value among C classes or categories with $C > 2$ (i.e. a multiclass problem), logistic regression can follow an iterative process in which the odds ratio for each category is computed by considering one category at each time and taking the set of remaining categories as a new class. However, a more natural and accurate extension to multiclass problems is done by directly considering a multinomial logistic regression. Like the binary logistic regression, the model now aims to approach the posterior probabilities of the C classes via linear functions in the predictors. In such a case, the model parameters are estimated by solving a set of independent binary regressions through variations in the maximum likelihood method (Engel, 1988). Although not widely used in thermal comfort research, multinomial logistic regression has been used to directly model TSV as function of the indoor air temperature (Haldi and Robinson, 2010).

Ordinal logistic regression However, when the dependent variable is ordinal - as is the case with TSV in thermal comfort research - ordinal logistic regression is needed (McCullagh, 1980). This follows the method of multinomial regression, but takes advantage of the additional knowledge contained in the order of the categories. A common technique to undertake ordinal logistic regression is the proportional odds method which works with cumulative probabilities. This method makes the assumption that the relationship measured through the odds between one category and another is the same for any pair of categories of the dependent variable. If this assumption is not met, the straightforward solution is still multinomial logistic regression. An example is the use of ordinal logistic regression to model overall workspace satisfaction as a function of indoor environmental parameters and building characteristics (Frontczak et al., 2012).

Decision tree The preceding three methods are variants on the fundamental idea of regression to create a mapping between dependent and independent variables. A Decision Tree (DT) model, on the other hand, is a method that creates a hierarchical tree graph based on how several independent variables partition a dependent or target variable. This partitioning reveals the strength of relationships in a dataset through the size of the split at each step. DT algorithms, of which there are many, recursively partition the data space into a number of simple regions following an optimal splitting criterion. This way of splitting the data space can be represented by a sequence of nodes and directed edges in a hierarchical structure, forming a tree. The partition algorithm starts at the root node of the tree, which will have no incoming edges. Starting from the root node, the data space splits into a number of regions, each one represented as a new node. The process is iterated, generating further new nodes from those previously created, each of which has exactly one incoming edge from its predecessor. Each branch of the tree finishes in a leaf node, which provides the category that best represents the corresponding region when the data cannot be split further.

For our analysis we use the most common DT algorithm: the C4.5 algorithm (Quinlan, 1986), which improves on the earlier ID3 algorithm. Inherent within both ID3 and C4.5 is the idea of information gain to optimise the partition process. This optimisation favours outcomes with higher information gain when undertaking the split, which leads to a division into regions of similar observations (purity per region). The information gain is measured through the difference in *entropy* before and after splitting; where the concept of entropy is related to the misclassification or impurity of a node and takes values in the range [0, 1]. If the elements of a node are equally divided into two or more categories, then the entropy is one. If all the elements in the node belong to the same category then the entropy is zero. So, the decision tree is constructed so that it minimises the entropy at the leaf nodes (ideally reaching the value of zero entropy). Given a categorisation C which divides the dataset S into categories $c_1 ... c_n$ and considering the proportion of observations in c_i being p_i, then the entropy of S is derived through the following equation:

$$Entropy(S) = \sum_{i=1}^{n} -p_i \log(p_i) \tag{4.3}$$

Random Forest A random forest (RF) is an ensemble of tree-based models. RF can be used for classification tasks when the base models are classification trees, or regression tasks when the base models are regression trees. For our analysis we use Breiman's RF algorithm, which is based on a bootstrap aggregation (or bagging) of tree models (Breiman, 2001). Bootstrapping is sub-sampling (with replacement) of a sample to infer the characteristic features of the population from which the sample is drawn, which are fundamentally unknown. Given the responses $Y = Y_1, ..., Y_m$ from the corresponding training set $X = X_1, ..., X_m$ a bagging tree is constructed by selecting B samples (sub-sampling with replacement) from (X, Y) and training a decision tree for each sample. Finally, the bagging tree is computed by either averaging all the resulting single trees (if Y is continuous) or taking their majority through a process where each tree is a vote (if Y is discrete).

RFs have several advantages over DTs: they run more efficiently on large data sets, provide more accurate predictions, avoid biases often associated with single DTs, handle missing data well and provide methods for balancing error in unbalanced data sets. For these reasons, RFs have proven to be outstanding predictive models in many classification and regression tasks.

4.3.2 Data

A description of the RP-884 database can be found in (De Dear et al., 1998; Dear and Brager, 2002), together with a meta-analysis of the data forming the ASHRAE adaptive equation as included in ASHRAE (2013). The data itself is available to download from the website of the University of Sydney.

Since the database has been standardized by de Dear and Brager allowing consistency of measured and calculated parameters, all the metrics (e.g. clothing insulation, operative temperature and metabolic rate) are used as presented in the database. For the analysis, we reduce the seven categories in the standard ASHRAE TSV scale to the following three classes (see Table 4.2):

- votes in the range of [-3, -1) considered as cold,
- votes in the three central categories, i.e. in the range of [-1, 1], regarded as neutral/comfortable per the usual definition of thermal comfort (ASHRAE, 2013),
- votes in the range of (1, 3] considered as hot.

The reduction to a 3-point scale is supported by the common use of the scale whereby excursions beyond the +1 and -1 limits are considered uncomfortable (Haldi and Robinson, 2010). The use of three categories instead of seven also has the benefit of improving the explanatory power of the statistical models used, by increasing the number of data points in each group on either side of -1 and +1.

Table 4.2: The seven-point ASHRAE scale of thermal comfort (top) converted into a simplified scale of thermal comfort (bottom) for the analysis.

How are you feeling right now?

Cold	Cool	Slightly cool	Neutral	Slightly warm	Warm	Hot
-3	-2	-1	0	1	2	3

How are you feeling right now?

Cold	Neutral	Hot
-1	0	1

A key distinction in method between that used to derive the ASHRAE adaptive model (De Dear et al., 1998; Dear and Brager, 2002) and ours, is the unit of analysis. While the ASHRAE model is derived by aggregating data at the building level, we directly use the raw data from the database and hence operate at the level of an individual occupant. While the building level was considered appropriate due to the similarities between the *building* *contextual factors* affecting subjective responses (such as availability and accessibility of personal control, view and connection to the outdoors, interior design, occupancy patterns and social constraints (O'Brien and Gunay, 2014)), this approach has the drawback of losing a great quantity of information in the process of aggregation. By using the raw data, we are able to use new techniques to investigate the effect of various predictors on the categorical response variable TSV.

For our analysis, we begin by including all the variables described in Section 4.2, except dry bulb and globe temperatures whose effect is contained within the operative temperature. The operative temperature is defined as the arithmetic mean of the air and mean radiant temperatures in the ASHRAE database. Since the adaptive model only applies to NV buildings with adult occupants, only data from these buildings are selected. The ASHRAE RP-884 database provides data from a total of 39 NV buildings over 8 climates (wet equatorial, humid subtropical, temperature marine, Mediterranean, tropical savanna, west coast marine, hot arid desert, semi-arid mid and high altitude). We further restrict the data to only outdoor temperatures within the ASHRAE applicability limits of 10 and 33.5°C, obtaining a total of 9,546 rows of observations. Since the data are already clean and ready to use, the only modification needed is to eliminate 1,289 rows of missing data (14% of the sample) resulting in a total of 8,257 rows available for analysis.

Variable selection Feature or variable selection is the process of selecting a subset of relevant features/variables from the data (Hastie et al., 2009), in order to:

- improve the interpretability of the data,
- reduce the effect of noise or collinearity,
- increase the predictive ability of the consequent statistical model,
- perform a computationally efficient data analysis.

We perform a correlation analysis to eliminate highly correlated variables from further analysis. Figure 4.5 shows the correlation matrix for the 7 predictor variables selected. This confirms the results of De Dear et al. (1998) and Nicol and Humphreys (2010), where clothing insulation is shown to be strongly inversely correlated with outdoor temperature. As expected in naturally ventilated buildings, T_{op} is strongly correlated with T_{out}. While SEX, MET, VA and RH are not found to be strongly correlated to T_{out}. Hence, we continue our analysis with the following independent variables: T_{op}, RH, VA, MET, SEX and we further include T_{out} to retain the main assumption of the adaptive hypothesis.

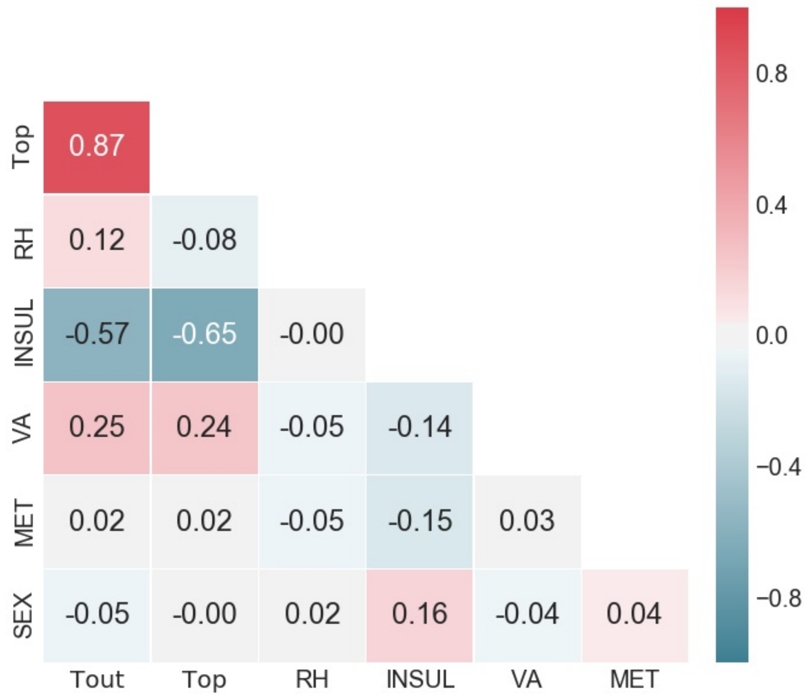


Figure 4.5: Correlation matrix for the selected variables. Each cell shows the Pearson coefficient, colour coded according to the strength of positive (red) and negative (blue) correlation.

4.3.3 Experimental study

In this section we report the results of the experiments carried out using the models discussed in Section 4.3.1 on the ASHRAE RP-884 data.

Model comparison The aim of the experiments is to find the model that best describes the RP-884 data, i.e. the model with the smallest prediction error. We use the Python programming language as a convenient vehicle for comparing the ability of the five models, discussed in Section 4.3.1. The independent variables are those selected in Section 4.3.2, while the dependent variable to be modelled is TSV as defined in Table 4.2. Fifty stratified randomized sets of training and test data are created using the function $sklearn.modelselection.StratifiedShuffleSplit()$ (Pedregosa et al., 2011). By using this function, the test sets preserve the percentage of samples for each class, i.e. the test and train sets have the same percentage of data in each of the three classes (cold, neutral, hot). The proportion of the dataset included in the test split is always 20% of the original sample. Model predictions coming from the training data are compared with the test data. Prediction errors for each model and for each set of training/test data are calculated using the $F1$ score implemented by the Python function $sklearn.metrics.f1score()$ (Pedregosa et al., 2011). $F1$ is a weighted average of the precision and recall scores, reaching its best value at 1 and worst one at 0. Prediction errors are defined as $1 - F1$.

Figure 4.6 shows a boxplot of the prediction errors associated with the 50 randomized sets of train and test data for each of the 5 models studied, i.e. each boxplot contains 50 error scores. Results fall into three clear groups: the logistic and multinomial logistic have the largest errors (mean equal to 0.42 and 0.40, respectively); the random forests classifier has the lowest error (mean error = 0.20); and the ordinal logistic and decision tree classifier are in the middle (mean equal to 0.27 and 0.26, respectively). It is noteworthy that the mean error rate of the RF classifier is 56% lower than that of the multinomial logistic regression, the best in class method used in the thermal comfort literature so far.

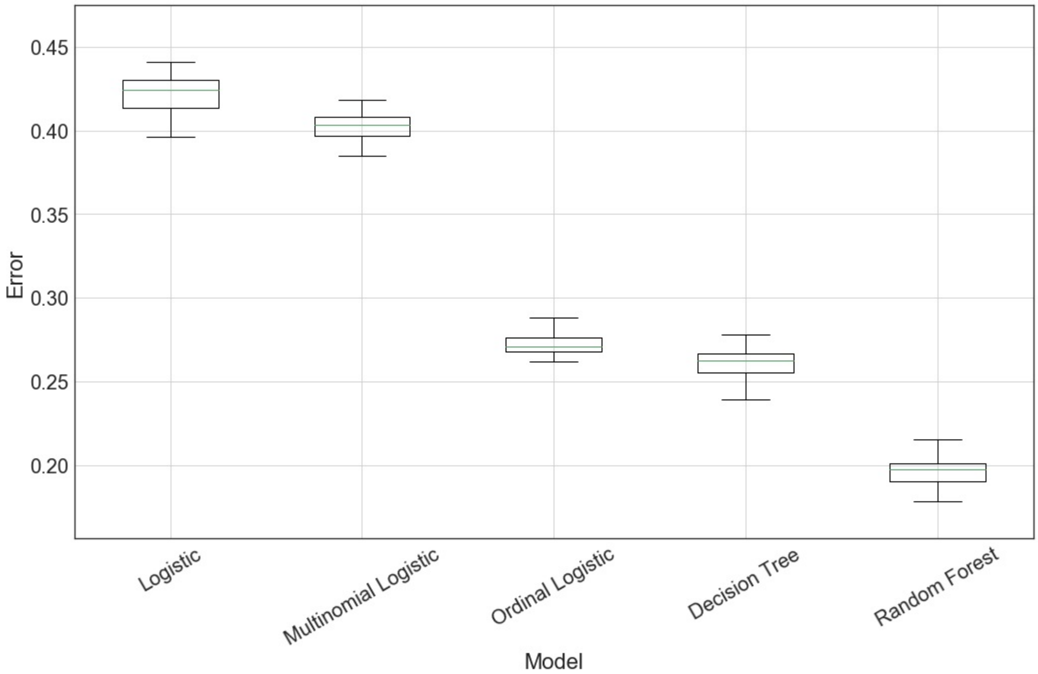


Figure 4.6: Boxplot of the prediction errors ($1 - F1$) associated with the different models. The box extends from the lower to upper quartile values of the data, with a line at the median. The whiskers extend from the box to show the range of the data.

Variable importance Having identified the RF classifier as the method with the least error, Figure 4.7 shows the relative importance of each studied variable as classified by the RF. This confirms the prevailing adaptive model by demonstrating that T_{op} and T_{out} are the most influential variables with importance scores of 37% and 23%, respectively.

It also shows that RH follows T_{out} with an importance score of 14%. This is suggestive of a weaker signal in determining thermal comfort compared to indoor temperature. It is therefore unsurprising that current methods such as multinomial logistic regression were unable to detect such a signal, given their considerably higher error rate in describing the data set.

Interestingly SEX is shown to not be significantly influential in our ranking. Given that VA and MET are factors that can be controlled by the occupants in NV buildings (see Section 4.2), we reduce the main predictor variables to the following three: T_{op}, T_{out} and RH.

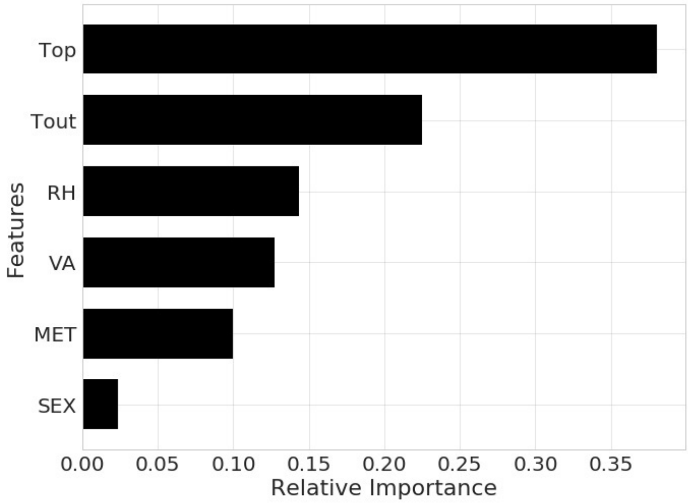


Figure 4.7: Relative importance of features as given by the RF classifier.

4.4 A new adaptive thermal comfort model

Sections 4.2 and 4.3 provide strong evidence that a humidity signal exists in adaptive thermal comfort. However, neither provides a clear route towards a practical formulation that can be easily interpreted and applied during the design of buildings. Hence, in this section, we derive a new adaptive model that frames the impact of *RH* within the familiar linear form of the current adaptive model.

To derive our new adaptive model, we use the ASHRAE RP-884 data and consider only neutral votes (as defined in our simplified scale in Table 4.2). To simplify the continuous nature of the humidity data, we cluster the neutral votes using the widely used k-means clustering (as implemented in the Python function *sklearn.cluster.KMeans*() (Sculley, 2010)). The k-means algorithm clusters data by trying to minimize the distance between data belonging to the same cluster while maximizing the distance between data belonging to different clusters. This leads to a clustering configuration of minimum variance within groups and maximum variance between different groups. This algorithm requires the specification of the number of clusters, which was set to 3. The algorithm was run 10 times, each with different random starting conditions to obtain the clusters. The k-means algorithm returns the following 3 clusters:

- High: $RH \geq 59\%$
- Medium: $37\% < RH < 59\%$
- Low: $RH \leq 37\%$

This clustering accords well with *Sterling's criteria* for human exposure to humidity in occupied buildings, which suggests that the optimal conditions to minimize risks to human health occur in the narrow range between 40-60% relative humidity (Sterling et al., 1985). Hence, the middle range in our clustering is the functional equivalent of *Sterling's Optimum Zone*, and the low and high ranges correspond to the non-optimal zones. To improve model readability, we simplify the clusters to convert the middle cluster to the range of 40-60%.

Within each *RH* cluster, we collate all the TSV votes into 1°C T_{out} x 1°C T_{op} grid bins. In order to meet the 80% acceptability criterion incorporated in the current model, we reject any bin with less than 80% of neutral votes, i.e. votes falling into the three central categories of the 7-point ASHRAE scale. Finally, we compute mean T_{op} and mean T_{out} for each grid bin. Now, by applying a simple linear regression to each cluster of RH, three linear models are obtained:

$$T_{op(RH \geq 60\%)} = 0.53 T_{out} + 12.85 \qquad (\pm 2.84) \tag{4.4}$$

with $N = 43$ and $R^2 = 0.84$.

Table 4.3: Results of the simple linear regression model for the high humidity cluster.

	coef.	SE	p-value	[95.0% conf. int.]
Intercept	12.8535	0.860	0.000	11.117 to 14.590
T_{out}	0.5347	0.037	0.000	0.461 to 0.609

$$T_{op(40\% < RH < 60\%)} = 0.53 T_{out} + 14.16 \qquad (\pm 3.70) \tag{4.5}$$

with $N = 67$ and $R^2 = 0.76$.

Table 4.4: Results of the simple linear regression model for the medium humidity cluster.

	coef.	SE	p-value	[95.0% conf. int.]
Intercept	14.1577	0.787	0.000	12.587 to 15.729
T_{out}	0.5280	0.037	0.000	0.454 to 0.602

$$T_{op(RH \leq 40\%)} = 0.52 T_{out} + 15.23 \qquad (\pm 4.40) \tag{4.6}$$

with $N = 64$ and $R^2 = 0.66$.

Table 4.5: Results of the simple linear regression model for the low humidity cluster.

	coef.	SE	p-value	[95.0% conf. int.]
Intercept	15.2301	0.995	0.000	13.240 to 17.220
T_{out}	0.5157	0.047	0.000	0.422 to 0.609

The temperature bands in the above equations are given by the prediction intervals. Here, we define a prediction interval as one in which future observations are likely to fall with 95.0% probability. Figure 4.8 shows the temperature bands for the 3 clusters together with the ASHRAE adaptive model in red.

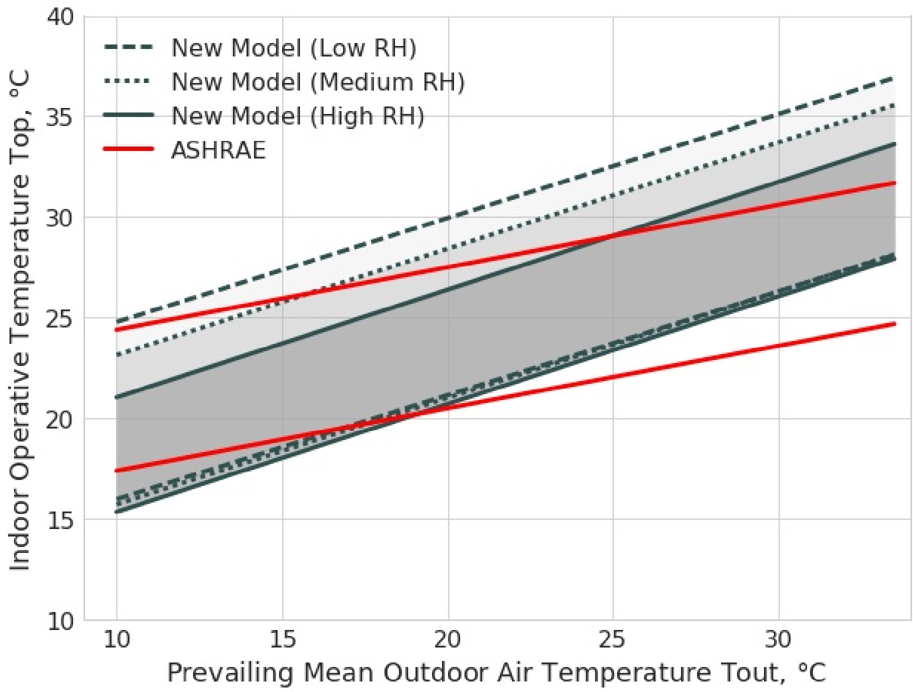


Figure 4.8: The proposed new, and existing, adaptive models.

The following major outcomes can be observed from the model in Figure 4.8:

- Comfort temperatures are generally higher and the gradient is much steeper, than those predicted by the current ASHRAE adaptive model.
- Comfort temperatures are lower when humidity is high throughout the range of T_{out}. The difference in comfort temperatures between high and low humidity environments is as high as 4°C.
- The smallest temperature acceptability range corresponds to a high relative humidity, while the acceptability range for a medium humidity is equal to the acceptability range defined in the ASHRAE adaptive model.

It is important to note at this point that while this formulation follows from the relatively simple process of regression, it relies on the evidence uncovered from the RF process demonstrated in Section 4.3 as well as the earlier analysis of thermal sensitivity in Section 4.2. Without these, the separation by *RH* would be arbitrary and meaningless. As a corollary, these independent lines of evidence preclude the creation of further *adaptive models* by the application of the method in this section to any of the other variables such as air velocity or gender, even if such models were deemed to be meaningful, without further new evidence.

4.5 Measuring the impact of the new adaptive comfort model

Section 4.4 derives a new adaptive comfort model that relates thermal comfort to not just outdoor temperature but also indoor relative humidity. This section considers the potential impact of designing naturally ventilated buildings using this new model by comparing it against the current model. The chosen building type is office since the vast majority of ASHRAE data comes from offices: 57% of the studies are in offices with a further 36% in both (offices + residential) buildings. The chosen performance metric is the widely used *count of overheating hours*, measured as the percentage of occupied hours above the maximum operative temperature threshold when using a given comfort model. Overheating is measured by implementing our new thermal comfort model within the well-established EnergyPlus (v8.7) simulation software and applying it to a building simulation case study, together with the current model. An implementation of the new adaptive comfort model is available via the public Python package *velleiacm*.

The implemented building model represents a NV office based on the Department of Energy reference models for the U.S. (Deru et al., 2011). The following adaptations were made to make it suitable for this study:

- Unlike the reference building, the office is set to be naturally ventilated and in free-running mode exclusively. This is needed to allow the application of adaptive models as specified in the ANSI/ASHRAE Standard 55-2013 (ASHRAE, 2013). To enable this change in operating mode, the following additional changes were made:
  - The original span of the building has been adapted from ∼ 18m to 12m.
  - Two ventilation schemes were modelled to account for the two most common natural ventilation modes: double-sided cross-ventilation and single-sided ventilation. For the former, all internal partitions are removed. For the latter, a single partition runs along the length of the building to provide a 6 m ventilated depth.
- The model is considered to be located at an intermediate level within a multi-floor office block. Both the ceiling and the floor have been considered adiabatic and no energy transfers are allowed except for heat storage.
- Surrounding buildings are considered at a 20 m distance with the same height as the zone under consideration.

Natural ventilation is modelled with an airflow network. Rather than simpler and more traditional methods, airflow networks allow the approximation of pressure-driven air exchanges with the outdoor environment or another zone by modelling the underlying physical laws in greater detail, accounting for wind and stack effects, bidirectional air flows in large openings and cross-ventilation among other phenomena. Windows are sized to a 20% window-to-wall ratio and the total openable area for natural ventilation is equal to 5% of the total floor area of the office. To compare comfort models, meta-programming of the simulation behaviour through the Energy Management System (EMS) functionality in EnergyPlus was implemented, as follows:

- Windows are opened if the following three conditions are met simultaneously: the zone is occupied, the neutrality temperature is surpassed and the external temperature is below the zone temperature. All temperatures are evaluated as operative temperatures.
- Both comfort models are implemented with two variants (i.e. there are a total of 4

variants). The variants are based on the interpretation of outdoor temperature in the models as evidenced in extant practice and ASHRAE recommendations. One variant uses the monthly mean outdoor temperature (*original*) and the other an exponentially weighted running mean with $\alpha = 0.8$ (*running mean*).

A number of *simulation model variants* are produced using a scripted building generator to cover a wide range of scenarios. These include:

- 13 of the 14 locations where the ASHRAE RP-884 NV buildings were surveyed (a weather file for Saidu in Pakistan could not be obtained),
- 4 different orientations (N/S, E/W, SE/NW and SW/NE - the building is symmetrical),
- 3 levels of shading (low, medium and high, i.e. 0, 0.5 and 1 times the required depth to shade the opening at noon during the summer solstice),
- and 3 window openable areas (3.5%, 5% and 6.5% of the office floor area).

Together with the different control algorithms based on the 2 adaptive models with the 2 formulations of the outdoor mean temperature, these result in a total of 1,872 model variants for each ventilation scheme (i.e. a total of 3,744 variants).

4.5.1 Simulation results

Figure 4.9 shows a summary of results from the simulations. It is clear that the new model produces considerably lower overheating than the current model and that there is little difference in whether monthly mean or running mean outdoor temperature is used in computing either adaptive model.

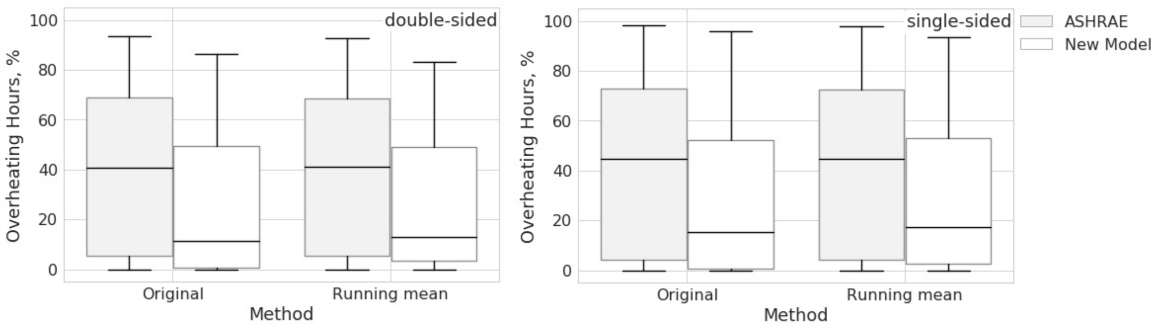


Figure 4.9: A comparison of overheating hours between the current ASHRAE model and the new model proposed in this paper for double-sided (left) and single-sided (right) offices. Each box-and-whisker plot represents data from 468 variants based on differing location, orientation, shading and window openable areas.

Figure 4.10 shows that the high levels of overheating observed in Figure 4.9 are primarily a function of the large diversity of climates represented in the data set. An interesting feature of Figure 4.10 is that the largest differences between the proposed new model and the current model are observed in climates with low humidity (e.g. Quetta, Karachi and Peshawar). Finally, the warmer the climate, the lower the predicted overheating in the new model compared to the current model. In other words, the new model significantly extends the potential range of operation for buildings in all climates, with the most in the warmest and least humid climates.

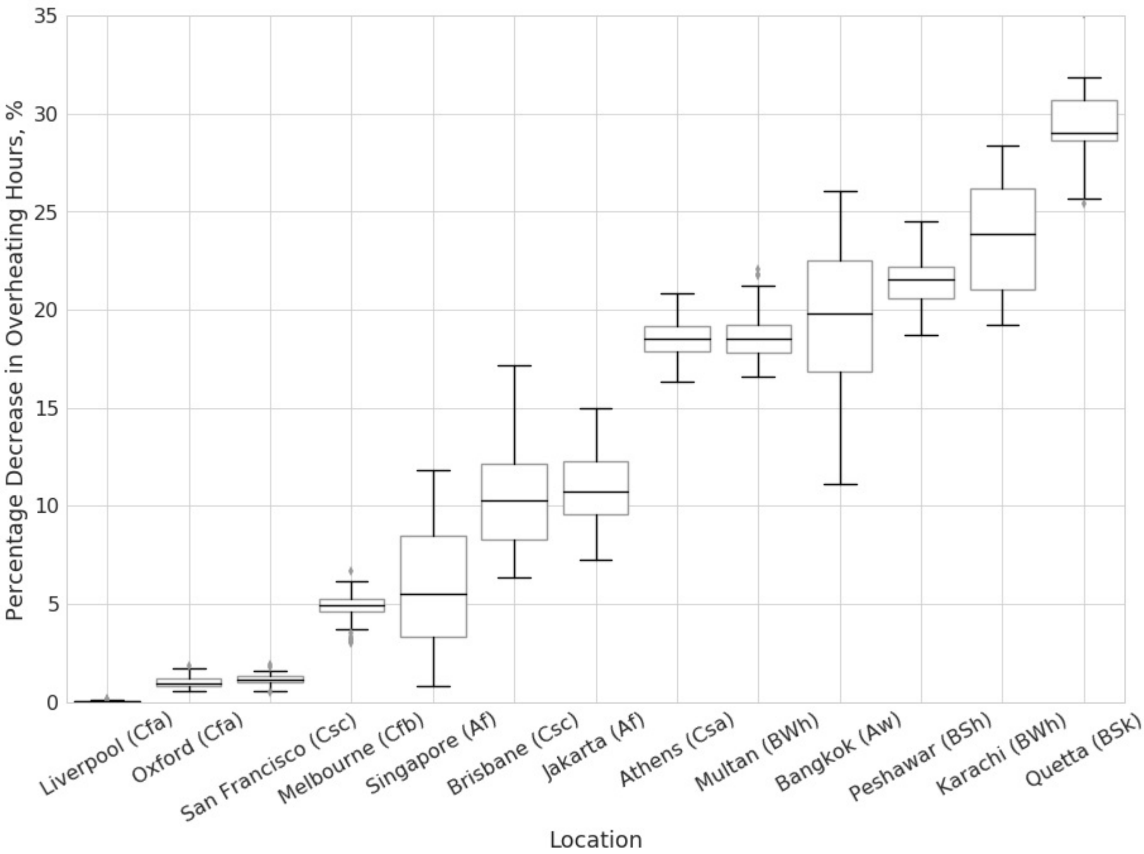


Figure 4.10: Rank-ordered percentage decrease in overheating hours when using the new adaptive model proposed in this paper in place of the current ASHRAE model. Letters within brackets show the Köppen Geiger climate classification (Kottek et al., 2006) for each location. The box-and-whisker plots represents data from a total of 3,744 simulations.

4.6 Discussion

Previous attempts to characterise the impact of humidity on the adaptive thermal comfort equation have found limited or no evidence of a change in comfort at varying levels of humidity. These are summarised below:

- A study clustering mean outdoor *RH* from ASHRAE (De Dear et al., 1998) and other (Humphreys, 1976) field data into low (< 63%), medium (64 – 75%) and high (> 75%) found that neutral temperatures, obtained using the Griffiths method, were only about 1°C lower for *RH* > 75% compared to the overall data (Nicol, 2004).
- A study deriving an adaptive comfort model for the hot-humid regions of South-East Asia found a similar comfort equation for NV buildings as the ASHRAE adaptive equation (Nguyen et al., 2012).
- Another study using the ASHRAE field data found that the regression coefficients of the adaptive equations for hot-humid (0.57) and hot-dry climates (0.58) were nearly double that of the ASHRAE model (0.31), and slightly lower for moderate climates (0.22) (Toe and Kubota, 2013). This study did not observe lower comfort limits at higher relative humidity for hot-humid climates. However, hot-dry climates were found to have larger comfortable temperature bands than hot-humid climates. The

authors suggest that this could be because it is easier to adapt when humidity is low, supported by their observation that in hot-dry climates, a higher indoor *RH* implies lower comfort temperatures. These results are very interesting and anticipate some of our results, although they do not offer the comprehensive explanation which we provide with our model.

One of the principal reasons suggested in the literature for the lack of a humidity signal in adaptive comfort models is that occupants in humid climates are usually well adapted to high humidity. The use of fans, opening of windows for increasing air movement, and wearing clothing that enhances evaporation of sweat have all been suggested as adaptive actions common in hot and humid climates (Ballantyne et al., 1977; Givoni et al., 2006; De Dear et al., 1991; Rijal et al., 2015; Chow et al., 2010).

In contrast, our new model shows that the impact of relative humidly cannot be neglected. This is supported by two independent lines of evidence both of which demonstrate that humidity plays a significant role in mediating adaptive thermal comfort. Although it is possible that the effect of humidity is mitigated by several adaptive actions, it is important to consider that, unlike air velocity, it cannot be directly controlled in NV buildings, as demonstrated in Figure 4.1. Hence, it is essential that the effect of humidity is explicitly incorporated within the design of such buildings.

4.7 Conclusions

Adaptive thermal comfort has been a breaking new paradigm which has changed the way of looking at thermal comfort in NV buildings. However, the model has remained essentially the same for the last 20 years and its simplicity, which was its initial strength, now poses some concerns. We highlight the principal concern as the lack of a signal for relative humidity. From a meta-analysis of the regression gradient using descriptive statistics from a large number of global studies, we demonstrate, for the first time, the clear importance of relative humidity in determining the sensitivity of occupants within the adaptive comfort paradigm. We produce a second, independent, line of evidence using a random forests process on high-resolution thermal comfort data from buildings across the world that strongly supports this initial finding. Finally, we use these data to derive a new adaptive model which incorporates relative humidity in three clusters, obtained via a k-means clustering of humidity conditions found within the data. Since the new model is formulated using the familiar linear relationship that designers are already accustomed to, it can be readily used for the design of low-energy naturally ventilated buildings around the world. We demonstrate the use of the new model for the design of a naturally ventilated building in each location from which the empirical data was sourced. Results show that our new model significantly increases the comfort envelope of naturally ventilated buildings since its prediction of overheating is 30% lower than that of the current model. Hence, the use of our model significantly extends the current adaptive comfort boundaries.

Acknowledgements

Daniel Fosas and Marika Vellei appreciate the support of the EPSRC *dCarb* centre (EP/L016869/1). Daniel Fosas is also funded by *laCaixa* Foundation.

Appendix

Table 4.6, Table 4.7 and Table 4.8 show key information about the studies included in the meta-analysis of Section 4.2.

Table 4.6: Main information for the field studies, included in the ASHRAE database, surveying naturally ventilated buildings free-running in summer.

ASHRAE Database No.	Köppen Climate	Location	Building Type	Survey Type	Survey Class	Sample Size
12	Csc	Brisbane, Australia	O	T	II	652
16	Cfb	Melbourne, Australia	O	T	II	582
27	Csa	Athens, Greece	R	L	II	1626
4	Aw	Bangkok, Thailand	O	T	II	392
33	Csc	San Francisco, USA	O	L and T	I	360
28	Cfa	Oxford, UK	O	L	III	877
18	BWh	Karachi, Pakistan	R and O	L	III	190
23	BSk	Quetta, Pakistan	R and O	L	III	492
20	BWh	Multan, Pakistan	R and O	L	III	437
21	BSh	Peshawar, Pakistan	R and O	L	III	556
25	Cfa	Saidu, Pakistan	R and O	L	III	568
7	Af	Jakarta, Indonesia	O	T	III	97
38	Cfa	Liverpool, UK	O	T	II	167
42	Af	Singapore	O	T	II	583

R=Residential, O=Office, T=Transverse, L=Longitudinal.

Table 4.7: Main information for the newly reviewed field studies included in the meta-analysis of the regression gradient. An empty space means that the information is not available.

Reference	Köppen Climate	Location	Building Type	Survey Type	Survey Class	Sample Size	Building Operation
Feriadi and Wong (2004)	Am/dry and rainy	Jogjakarta, Indonesia	R	L	II	525	NV
Karyono (2008)	Af/rainy	Bandung, Indonesia	E	L	III	200	MM/free-running mode
Karyono et al. (2015)	Am/rainy	Jakarta, Indonesia	Cathedral	T	III	70	NV
Karyono et al. (2015)	Am/rainy	Jakarta, Indonesia	Museum	T	III	77	NV
Ogbonna and Harris (2008)	Aw/rainy	Jos, Nigeria	R and E	L	II	200	NV
Moujalled et al. (2008)	Cfb/summer	Lyon, France	O	T	II	221	NV
Yang and Zhang (2008)	Cfa/summer	Nanjing, Shanghai, Wuhan, Changsha and Jiujiang, China	R and O	L	II	129	NV
Farghal and Wagner (2010)	BWh/autumn and spring	Greater Cairo, Egypt	E and O	L		644	NV
Farghal and Wagner (2010)	BWh/autumn and spring	Greater Cairo, Egypt	E and O	L		638	NV
Farghal and Wagner (2010)	BWh/autumn and spring	Greater Cairo, Egypt	E and O	L		656	NV
Farghal and Wagner (2010)	BWh/autumn and spring	Greater Cairo, Egypt	E and O	L		751	NV
Djamila et al. (2013)	Af/all seasons	Kota Kinabalu, Malaysia	R	L	II	890	NV
Indraganti et al. (2013b)	As/dry and rainy	Chennai, India	O	T	II	207	MM/free-running mode
Indraganti et al. (2013b)	BSh/dry and rainy	Hyderabad, India	O	T	II	352	MM/free-running mode
Mishra and Ramgopal (2015a)	Aw/dry	Kharagpur, India	E	L	III	533	NV

Table 2.7: Continued

Indraganti et al. (2013a)	Cfa/summer	Tokyo, Japan	O	T	II	423	MM/free-running mode
Gómez-Azpeitia et al. (2012)	BWh/summer	Hermosillo, Mexico	R	T	II	143	NV
Gómez-Azpeitia et al. (2012)	BWh/summer	Mexicali, Mexico	R	T	II	174	NV
Gómez-Azpeitia et al. (2012)	Aw/dry	Merida, Mexico	R	T	II	150	NV
Gómez-Azpeitia et al. (2012)	Aw/dry	Colima, Mexico	R	T	II	196	NV
Rijal (2014)	Cfa/summer	Kanto region, Japan	R	T	III	1915	MM/free-running mode
Luo et al. (2015)	Cwa/all seasons	Shenzhen, China	O	T	III	513	MM/free-running mode
Mustapa et al. (2016)	Cfa/summer	Fukuoka, Japan	O	T	III	81	MM/free-running mode
Rijal et al. (2017)	Cfa/all seasons	Tokyo and Yokohama, Japan	O	T	II	422	MM/free-running mode
Yan et al. (2017)	Cfa/summer	Nanjing, Shanghai and Chongqing, China	R	L	II		NV
Yan et al. (2017)	Dwa/summer	Harbin, Changchun and Shenyang, China	R	L	II		NV
Yan et al. (2017)	Dfa/summer	Beijing, Xi'an and Zhengzhou, China	R	L	II		NV
Yan et al. (2017)	Cwa/summer	Guangzhou, Nanning and Haikou, China	R	L	II		NV
Rijal et al. (2010)	sub-tropical, temperate and cool/summer	Banke, Bhaktapur, Dhading, Kaski and Solukhumbu, Nepal	R	L	III	2180	NV
Mishra and Ramgopal (2014)	Aw/dry	Kharagpur, India	E	L	III	338	NV

Table 2.7: Continued

Liu et al. (2017)	Cfa/spring	Chongqing, Chengdu, Wuhan, Nanjing, Hangzhou and Changsha, China	R	L	II	2965	NV
Liu et al. (2017)	Cfa/summer	Chongqing, Chengdu, Wuhan, Nanjing, Hangzhou and Changsha, China	R	L	II	2521	NV
Liu et al. (2017)	Cfa/autumn	Chongqing, Chengdu, Wuhan, Nanjing, Hangzhou and Changsha, China	R	L	II	3385	NV
Bouden and Ghrab (2005)	Csa/all seasons	Kef, Tunisia	R and O	T	II		NV
Bouden and Ghrab (2005)	Csa/all seasons	Tunis, Tunisia	R and O	T	II		NV
Bouden and Ghrab (2005)	BSh/all seasons	Sfax, Tunisia	R and O	T	II		NV
Bouden and Ghrab (2005)	BWh/all seasons	Gabes, Tunisia	R and O	T	II		NV
Bouden and Ghrab (2005)	BWh/all seasons	Gafsa, Tunisia	R and O	T	II		NV
Dhaka et al. (2015)	BSh/winter	Jaipur, India	R and O		II	610	NV
Dhaka et al. (2015)	BSh/moderate season	Jaipur, India	R and O		II	346	NV
Dhaka et al. (2015)	BSh/summer and monsoon	Jaipur, India	R and O		II	855	NV
Indraganti (2010b)	BSh/summer	Hyderabad, India	R	T	II	1405	NV
Indraganti (2010b)	BSh/monsoon	Hyderabad, India	R	T	II	1334	NV
Indraganti (2010b)	BSh/monsoon	Hyderabad, India	R	T	II	1223	NV
LACHIREDDI et al. (2017)	Am/dry	Calicut, India	R	T	III	735	NV

R=Residential, O=Office, T=Transverse, L=Longitudinal.

Table 4.8: Main data used in the meta-analysis of the regression gradient. An empty space means that the information is not available.

Reference	Indoor Temperature Metric	$\mu(T_i)$	$\sigma(T_i)$	$\mu(RH)$	$\sigma(RH)$	Linear Regression Type	a	b	R^2
Feriadi and Wong (2004)	T_{op}	29.8	1.4	68.6	6.6	Simple	0.59	-17.21	0.18
Karyono (2008)	T_{op}	28.9	1.5	59.8	6.8	Simple	0.31	-7.97	0.68
Karyono et al. (2015)	T_{db}	28.8	1.1	74.3	2.8	Simple	1.05	-29.02	0.90
Karyono et al. (2015)	T_{db}	29.7	1.1	74.1	3.8	Simple	0.68	-18.90	0.56
Ogbonna and Harris (2008)	T_{op}	26.5	2.1	72.1	5.6	Weighted Binned	0.36	-9.43	0.32
Moujalled et al. (2008)	T_{op}	27.3	2.8	43.5	8.5	Weighted Binned	0.21	-4.93	0.82
Yang and Zhang (2008)	T_{op}	33.3	2.4	74.0	11.6	Simple	0.25	-7.16	0.47
Farghal and Wagner (2010)	T_{db}	25.6	2.3	42.0	6.1	Simple	0.17	-4.17	0.19
Farghal and Wagner (2010)	T_{db}	29.8	3.4	35.5	10.1	Simple	0.24	-5.67	0.41
Farghal and Wagner (2010)	T_{db}	25.0	2.1	52.0	4.1	Simple	0.20	-4.73	0.16
Farghal and Wagner (2010)	T_{db}	24.7	3.9	37.5	5.7	Simple	0.17	-3.63	0.36
Djamila et al. (2013)	T_{db}	30.7	1.5	70.7	6.4	Simple	0.39	-11.87	0.17
Indraganti et al. (2013b)	T_g	30.1	2.6	57.2	8.8	Simple	0.31	-8.17	0.29
Indraganti et al. (2013b)	T_g	29.4	2.7	47.2	13	Simple	0.22	-5.68	0.17
Mishra and Ramgopal (2015a)	T_{op}	29.3	3.0	61.9	16.9	Weighted Binned	0.22	-6.50	0.73

Table 2.8: Continued

Indraganti et al. (2013a)	T_g	29.4	1.5	52.6	6.4	Simple	0.31	-7.95	0.36
Gómez-Azpeitia et al. (2012)	T_{db}	33.8	2.9	41.3	9.8	Simple	0.18	-4.90	
Gómez-Azpeitia et al. (2012)	T_{db}	33.4	4.1	28.5	9.4	Simple	0.13	-3.31	0.23
Gómez-Azpeitia et al. (2012)	T_{db}	34.1	2.3	41.0	7.3	Simple	0.17	-3.77	
Gómez-Azpeitia et al. (2012)	T_{db}	29.9	2.1	42.2	9.5	Simple	0.29	-7.51	
Rijal (2014)	T_{db}	28.4	2.3	64.4	8.5	Simple	0.19	-4.81	0.14
Luo et al. (2015)	T_{op}	23.2	2.6	63.1	11.6	Weighted Binned	0.09	-1.97	
Mustapa et al. (2016)	T_{op}	28.1	1	75.9	5.1	Simple	0.49	-13.1	0.21
Rijal et al. (2017)	T_g	25	1.9	45	11	Simple	0.18	-4.6	0.25
Yan et al. (2017)	T_{op}	29.4	2.7	68.3	4.4	Binned	0.36	-9.80	0.96
Yan et al. (2017)	T_{op}	24.4	2.1	62.8	4	Binned	0.19	-4.93	0.87
Yan et al. (2017)	T_{op}	28.6	3.4	63.1	5.3	Binned	0.24	-6.55	0.89
Yan et al. (2017)	T_{op}	29.7	2.2	66.8	4.2	Binned	0.13	-3.68	0.77
Rijal et al. (2010)	T_g	24.5	5.1	60.7	13.4	Simple	0.08	-1.95	0.83
Mishra and Ramgopal (2014)	T_{op}	29.3	3.0	61.9	16.9	Weighted Binned	0.22	-6.50	0.73

Table 2.8: Continued

Liu et al. (2017)	T_{db}	20.4	4.9	66.9	14.9	Binned	0.06	-1.2	0.95
Liu et al. (2017)	T_{db}	29.0	2.9	70.8	9.9	Binned	0.16	-3.76	0.93
Liu et al. (2017)	T_{db}	21.1	6.0	67.1	12.9	Binned	0.06	-1.52	0.97
Bouden and Ghrab (2005)	T_g	20.5	9.2	63	15	Simple	0.17	-3.62	0.84
Bouden and Ghrab (2005)	T_g	22.2	3.6	57	5	Simple	0.16	-3.18	0.50
Bouden and Ghrab (2005)	T_g	22.8	4.7	64	6	Simple	0.16	-3.27	0.57
Bouden and Ghrab (2005)	T_g	24.1	4	56	8	Simple	0.11	-2.31	0.29
Bouden and Ghrab (2005)	T_g	21.9	5.8	52	9	Simple	0.17	-3.60	0.74
Dhaka et al. (2015)	T_{db}	21.3	3.2	40.6	13.5	Simple	0.17	-4.39	0.20
Dhaka et al. (2015)	T_{db}	28.9	3.1	27.7	6.4	Simple	0.14	-3.89	0.11
Dhaka et al. (2015)	T_{db}	31.8	2.5	49.1	23.0	Simple	0.30	-8.79	0.38
Indraganti (2010b)	T_g	34.5	1.8	27.0	9.0	Simple	0.22	-5.93	0.42
Indraganti (2010b)	T_g	31.2	1.2	53.0	6.0	Simple	0.28	-8.30	0.40
Indraganti (2010b)	T_g	30.7	1.1	55.0	6.0	Simple	0.17	-4.67	0.25
LACHIREDDI et al. (2017)	T_{op}	31.7	2.2	65.7	7.2	Binned	0.56	-16.95	0.90

References

ASHRAE. 2013. *Standard 55:2013 – Thermal Environmental Conditions for Human Occupancy (ANSI Approved)*. American Society of Heating, Refrigerating and Air-Conditioning Engineers.

ASTM. 2012. *ASTM D6245:2012 – Standard Guide for Using Indoor Carbon Dioxide Concentrations to Evaluate Indoor Air Quality and Ventilation*. ASTM International.

The Effects of Household Characteristics and Energy Use Consciousness on the Effectiveness of Real-Time Energy Use Feedback: A Pilot Study. 2006.

Andersen, R. K. 2012. The influence of occupants' behaviour on energy consumption investigated in 290 identical dwellings and in 35 apartments. *10th International Conference on Healthy Buildings*.

Ansanay-Alex, G. 2013. Estimating Occupancy Using Indoor Carbon Dioxide Concentrations Only in an Office Building: a Method and Qualitative Assessment.

BEIS. 2013. *Energy Consumption in the UK*. UK Government department for business, energy & industrial strategy.

Boerstra, A. C., Hoof, J. van, and Weele, A. M. van. 2015. A new hybrid thermal comfort guideline for the Netherlands: background and development. *Architectural Science Review* 58 (1), pp. 24 – 34. DOI: 10.1080/00038628.2014.971702.

Brager, G. and Dear, R. J. de. 1998. Thermal adaptation in the built environment: a literature review. *Energy and Buildings* 27 (1), pp. 83 – 96. DOI: 10.1016/S0378-7788(97)00053-4.

Brager, G., Paliaga, G., and De Dear, R. 2004. Operable windows, personal control and occupant comfort.

Buchanan, K., Russo, R., and Anderson, B. 2015. The question of energy reduction: The problem(s) with feedback. *Energy Policy* 77, pp. 89 – 96. DOI: 10.1016/j.enpol.2014.12.008.

Cao, B., Zhu, Y., Ouyang, Q., Zhou, X., and Huang, L. 2011. Field study of human thermal comfort and thermal adaptability during the summer and winter in Beijing. *Energy and Buildings* 43 (5). Tackling building energy consumption challenges – Special Issue of ISHVAC 2009, Nanjing, China, pp. 1051 – 1056. DOI: 10.1016/j.enbuild.2010.09.025.

Cao, B., Zhu, Y., Li, M., and Ouyang, Q. 2014. Individual and district heating: A comparison of residential heating modes with an analysis of adaptive thermal comfort. *Energy and Buildings* 78, pp. 17 – 24. DOI: 10.1016/j.enbuild.2014.03.063.

Chiang, T., Natarajan, S., and Walker, I. 2012. A laboratory test of the efficacy of energy display interface design. *Energy and Buildings* 55. Cool Roofs, Cool Pavements, Cool Cities, and Cool World, pp. 471 – 480. DOI: 10.1016/j.enbuild.2012.07.026.

Chiang, T., Mevlevioglu, G., Natarajan, S., Padget, J., and Walker, I. 2014. Inducing [sub]conscious energy behaviour through visually displayed energy information: A case study in university accommodation. *Energy and Buildings* 70, pp. 507 – 515. DOI: 10.1016/j.enbuild.2013.10.035.

Daniel, L., Williamson, T., Soebarto, V., and Chen, D. 2015. Learning from thermal mavericks in Australia: comfort studies in Melbourne and Darwin. *Architectural Science Review* 58 (1), pp. 57–66. DOI: 10.1080/00038628.2014.976537.

Dear, R. de and Brager, G. 2001. The adaptive model of thermal comfort and energy conservation in the built environment. *International Journal of Biometeorology* 45 (2), pp. 100–108. DOI: 10.1007/s004840100093.

Delmas, M. and Kaiser, W. 2014. *Behavioral Responses to Real-time Individual Energy Usage Information: A Large Scale Experiment*. Prepared for the California Air Resources Board and the California Environmental Protection Agency.

EN. 2007. *EN 15251:2007 – Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics*. European Standard.

Emeakaroha, A., Ang, C. S., Yan, Y., and Hopthrow, T. 2014. Integrating persuasive technology with energy delegates for energy conservation and carbon emission reduction in a university campus. *Energy* 76, pp. 357–374. DOI: 10.1016/j.energy.2014.08.027.

Gram-Hanssen, K. 2010. Residential heat comfort practices: understanding users. *Building Research & Information* 38 (2), pp. 175–186. DOI: 10.1080/09613210903541527.

Haldi, F. and Robinson, D. 2010. On the unification of thermal perception and adaptive actions. *Building and Environment* 45 (11), pp. 2440–2457. DOI: 10.1016/j.buildenv.2010.05.010.

Hong, S. H., Gilbertson, J., Oreszczyn, T., Green, G., and Ridley, I. 2009. A field study of thermal comfort in low-income dwellings in England before and after energy efficient refurbishment. *Building and Environment* 44 (6), pp. 1228–1236. DOI: 10.1016/j.buildenv.2008.09.003.

Huebner, G. M., Cooper, J., and Jones, K. 2013. Domestic energy consumption—What role do comfort, habit, and knowledge about the heating system play? *Energy and Buildings* 66, pp. 626–636. DOI: 10.1016/j.enbuild.2013.07.043.

Hwang, R.-L., Cheng, M.-J., Lin, T.-P., and Ho, M.-C. 2009. Thermal perceptions, general adaptation methods and occupant's idea about the trade-off between thermal comfort and energy saving in hot–humid regions. *Building and Environment* 44 (6), pp. 1128–1134. DOI: 10.1016/j.buildenv.2008.08.001.

IEA. 2015. *Key World Energy Statistics*. International Energy Agency.

ISO. 2005. *ISO 7730:2005 – Ergonomics of the thermal environment: Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria*. International Organization for Standardization.

Indraganti, M. 2010b. Using the adaptive model of thermal comfort for obtaining indoor neutral temperature: Findings from a field study in Hyderabad, India. *Building and Environment* 45 (3), pp. 519–536. DOI: 10.1016/j.buildenv.2009.07.006.

Indraganti, M. 2011. Thermal comfort in apartments in India: Adaptive use of environmental controls and hindrances. *Renewable Energy* 36 (4), pp. 1182–1189. DOI: 10.1016/j.renene.2010.10.002.

Jevons, R., Carmichael, C., Crossley, A., and Bone, A. 2016. Minimum indoor temperature threshold recommendations for English homes in winter – A systematic review. *Public Health* 136, pp. 4 – 12. DOI: 10.1016/j.puhe.2016.02.007.

Juodis, E., Jaraminiene, E., and Dudkiewicz, E. 2009. Inherent variability of heat consumption in residential buildings. *Energy and Buildings* 41 (11), pp. 1188 – 1194. DOI: 10.1016/j.enbuild.2009.06.007.

Karjalainen, S. 2009. Thermal comfort and use of thermostats in Finnish homes and offices. *Building and Environment* 44 (6), pp. 1237 – 1245. DOI: 10.1016/j.buildenv.2008.09.002.

Karjalainen, S. and Koistinen, O. 2007. User problems with individual temperature control in offices. *Building and Environment* 42 (8), pp. 2880 – 2887. DOI: 10.1016/j.buildenv.2006.10.031.

Kavousian, A., Rajagopal, R., and Fischer, M. 2013. Determinants of residential electricity consumption: Using smart meter data to examine the effect of climate, building characteristics, appliance stock, and occupants' behavior. *Energy* 55, pp. 184 – 194. DOI: 10.1016/j.energy.2013.03.086.

Liu, J., Yao, R., and McCloy, R. 2012. A method to weight three categories of adaptive thermal comfort. *Energy and Buildings* 47, pp. 312 – 320. DOI: 10.1016/j.enbuild.2011.12.007.

Liu, J., Yao, R., and McCloy, R. 2014. An investigation of thermal comfort adaptation behaviour in office buildings in the UK. *Indoor and Built Environment* 23 (5), pp. 675 – 691. DOI: 10.1177/1420326X13481048.

Lohr, L. L. 2000. Designing the instructional interface. *Computers in Human Behavior* 16 (2), pp. 161 – 182. DOI: 10.1016/S0747-5632(99)00057-6.

McMakin, A. H., Malone, E. L., and Lundgren, R. E. 2002. Motivating Residents to Conserve Energy without Financial Incentives. *Environment and Behavior* 34 (6), pp. 848–863. DOI: 10.1177/001391602237252.

Mishra, A. K. and Ramgopal, M. 2013. Field studies on human thermal comfort — An overview. *Building and Environment* 64, pp. 94 – 106. DOI: 10.1016/j.buildenv.2013.02.015.

Nicol, F. and Humphreys, M. 2010. Derivation of the adaptive equations for thermal comfort in free-running buildings in European standard EN15251. *Building and Environment* 45 (1). International Symposium on the Interaction between Human and Building Environment Special Issue Section, pp. 11 – 17. DOI: 10.1016/j.buildenv.2008.12.013.

Nicol, F. and Roaf, S. 1996. Pioneering new indoor temperature standards: the Pakistan project. *Energy and Buildings* 23 (3). PLEA '94 International Conference, pp. 169 – 174. DOI: 10.1016/0378-7788(95)00941-8.

Nicol, J. F. and Humphreys, M. A. 2002. Adaptive thermal comfort and sustainable thermal standards for buildings. *Energy and Buildings* 34 (6). Special Issue on Thermal Comfort Standards, pp. 563 – 572. DOI: 10.1016/S0378-7788(02)00006-3.

O'Brien, W. and Gunay, H. B. 2014. The contextual factors contributing to occupants' adaptive comfort behaviors in offices – A review and proposed modeling framework. *Building and Environment* 77, pp. 77–87. DOI: 10.1016/j.buildenv.2014.03.024.

O'Neill, M. J. 1994. Work Space Adjustability, Storage, And Enclosure As Predictors Of Employee Reactions And Performance. *Environment and Behavior* 26 (4), pp. 504–526. DOI: 10.1177/001391659402600403.

Oseland, N. A. 1994. A comparison of the predicted and reported thermal sensation vote in homes during winter and summer. *Energy and Buildings* 21 (1), pp. 45–54. DOI: 10.1016/0378-7788(94)90015-9.

Peschiera, G., Taylor, J. E., and Siegel, J. A. 2010. Response–relapse patterns of building occupant electricity consumption following exposure to personal, contextualized and occupant peer network utilization data. *Energy and Buildings* 42 (8), pp. 1329–1336. DOI: 10.1016/j.enbuild.2010.03.001.

Rijal, H. B., Yoshida, H., and Umemiya, N. 2010. Seasonal and regional differences in neutral temperatures in Nepalese traditional vernacular houses. *Building and Environment* 45 (12), pp. 2743–2753. DOI: 10.1016/j.buildenv.2010.06.002.

Santin, O. G., Itard, L., and Visscher, H. 2009. The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock. *Energy and Buildings* 41 (11), pp. 1223–1232. DOI: 10.1016/j.enbuild.2009.07.002.

Schweiker, M. and Shukuya, M. 2011. Investigation on the effectiveness of various methods of information dissemination aiming at a change of occupant behaviour related to thermal comfort and exergy consumption. *Energy Policy* 39 (1), pp. 395–407. DOI: 10.1016/j.enpol.2010.10.017.

Schweiker, M., Brasche, S., Bischof, W., Hawighorst, M., Voss, K., and Wagner, A. 2012. Development and validation of a methodology to challenge the adaptive comfort model. *Building and Environment* 49, pp. 336–347. DOI: 10.1016/j.buildenv.2011.08.002.

Urban, B. and Gomez, C. 2013. A Case for Thermostat User Models. *13th Conference of International Building Performance Simulation Association*.

Vine, D., Buys, L., and Morris, P. 2013. The Effectiveness of Energy Feedback for Conservation and Peak Demand: A Literature Review. *Open Journal of Energy Efficiency* 2 (1), pp. 7–15. DOI: 10.4236/ojee.2013.21002.

Wang, Z., Zhang, L., Zhao, J., He, Y., and Li, A. 2011. Thermal responses to different residential environments in Harbin. *Building and Environment* 46 (11), pp. 2170–2178. DOI: 10.1016/j.buildenv.2011.04.029.

Wilhite, H. and Ling, R. 1995. Measured energy savings from a more informative energy bill. *Energy and Buildings* 22 (2), pp. 145–155. DOI: 10.1016/0378-7788(94)00912-4.

Wood, G. and Newborough, M. 2003. Dynamic energy-consumption indicators for domestic appliances: environment, behaviour and design. *Energy and Buildings* 35 (8), pp. 821–841. DOI: 10.1016/S0378-7788(02)00241-4.

Zhou, X., Ouyang, Q., Zhu, Y., Feng, C., and Zhang, X. 2014. Experimental study of the influence of anticipated control on human thermal sensation and thermal comfort. *Indoor Air* 24 (2), pp. 171–177. DOI: `10.1111/ina.12067`.

Postscript

Chapter 4 reviews all the statistical methods previously used (linear regression, Griffiths method and logistic regression) in the larger context of adaptive thermal comfort research and further expands some of the critical reflections highlighted in the previous two Chapters.

It provides new statistical evidence showing that the Griffiths method is not able to correctly predict occupants neutral temperatures and that linear and logistic regression can be successfully replaced by the use of new and more powerful statistical modelling techniques, such as decision tree and random forest.

The work presented in this chapter represents the main theoretical contribution of this thesis and, being derived from field data collected all over the world, has a global geographical scope and importance. It introduces and reviews some important concepts and statistical methods used in thermal comfort research which are useful to better understand and model adaptive thermal comfort. It is therefore expected to influence the way thermal comfort field data will be processed and analysed in the future.

Chapter 5

Conclusions and Further Work

5.1 Conclusions

This thesis investigates adaptive thermal comfort through the use of datasets either collected during previous studies or obtained during field monitoring planned and performed over the course of this PhD. One motivation for the present work lies in the fact that the ASHRAE and European adaptive models, which have radically influenced thermal comfort modelling, have remained essentially unchanged in the last 20 years. Due to the simple hypotheses on which they are built on, they now exhibit limitations in accurately predicting indoor thermal comfort.

This thesis builds up from the analyses of the thermal comfort data collected as part of two field studies (reported in Chapter 2 and Chapter 3) and identifies in the use of the concept of neutral temperature a major limitation of the current adaptive models. Chapter 2 shows the difficulties in correctly defining neutral temperatures by applying the two most commonly used methods in the thermal comfort literature, i.e. simple linear regressions and Griffiths method. Chapter 3 completely bypasses the problem of defining a neutral temperature by modelling thermal comfort using logistic regression. All these methods are then re-considered in Chapter 4 which, using global data, shows that the Griffiths method is unable to correctly predict occupant neutral temperatures. Additionally, Chapter 4 discusses other statistical methods used in thermal comfort research, including simple linear and simple logistic regression. The multinomial logistic regression method is found to be the best in class method used to predict thermal comfort. The analyses conducted using new statistical modelling techniques show that the use of a random forest classifier leads to a reduction of the error rate by 56% compared to the multinomial logistic regression.

The results presented in this thesis demonstrate that thermal comfort field data, collected up to 50 years ago, can be re-analysed with innovative statistical techniques providing new insights and more accurate models. These findings are expected to have a major influence on the way thermal comfort data will be analysed in the future and on how new adaptive comfort models will be derived. Nevertheless, this work also shows that new long-term field monitoring studies are an important source of information on the prevailing environmental conditions within buildings and on the drivers and effects of occupant adaptive behaviours and comfort.

In the following, we conclude this thesis by recalling the principal research objectives set at the beginning of this thesis and by summarizing the findings. As always in research, many of these findings bring new research questions. Hence, there is still much research to be done in the domain of adaptive thermal comfort; some lines of research are proposed at the end.

5.1.1 The importance of relative humidity

The ASHRAE and European adaptive models have been derived without providing a strong theoretical explanation for the exclusions of all the traditional Fanger's basic thermal comfort parameters, with the exception of the air and radiant temperatures. In **Chapter 2**, using global data we demonstrate, for the first time, that the main limitation of the ASHRAE model is the lack of a signal for relative humidity, which is a key variable in determining physiological thermal comfort. Although the effect of humidity is possibly mitigated by several adaptive actions, it cannot be directly controlled in naturally ventilated buildings. Hence, it is essential that the effect of humidity is explicitly included in the design of such buildings. We derive a new designer-friendly adaptive model that incorporates relative humidity in three clusters, obtained via a k-means clustering of humidity conditions found within the data.

We demonstrate the use of the new model for the design of a naturally ventilated building in each location from which the original empirical ASHRAE data were sourced. Results show that our new model significantly increases the comfort envelope of naturally ventilated buildings since its prediction of overheating is on average 30% lower than that of the current model. Hence, the use of our model extends the range of acceptable indoor conditions for designing low-energy naturally-conditioned buildings all over the world.

5.1.2 Overheating and air quality problems

The validity and applicability of the Europen adaptive model needs to be tested for the case of residential occupants in UK. Hence, in **Chapter 3** we use the results of a longitudinal thermal comfort field study in residential homes in UK to verify the ability of the European adaptive model to correctly predicting thermal comfort of British residential occupants. The collected thermal comfort survey data are validated against the European adaptive model and the results indicate that the European model underestimates discomfort in warm conditions. This suggests that a major reformulation of the European adaptive model is required. A unique model cannot accommodate the different forms of adaptation of the European population and is not able to reflect the variability of the European climate.

We also report the results of a long-term monitoring study of environmental quality and air quality in vulnerable and non-vulnerable households in UK. We show that, according to the CIBSE adaptive overheating criteria, overheating is occurring in the monitored homes, particularly and disproportionately in the households with vulnerable occupants. The experiment was deliberately designed through the choice of its location and type of building to make overheating unlikely. Yet, it was found in 38% of the vulnerable homes, and even if the monitored summers were not extreme and did not contain prolonged heat waves. This is an important finding which gives new insight on the dangerous impact of rising temperatures on the comfort of the most vulnerable part of the population. There was also a statistically significant difference in the survey-reported attitudes to window opening between vulnerable and non-vulnerable households, and this conclusion was supported by CO_2 measurements in the homes. In fact, the vulnerable homes were found to have worse indoor air quality, suggesting that overheating might be solved with better indoor ventilation. Hence, overheating cases can be tackled through behavioural changes only, without alterations to the homes and thus entailing zero capital cost.

5.1.3 The effect of real-time feedback

We consider the role of the adaptive models in a future built environment where feedback are expected to be a major aspect of the smart meter roll-out across the world. In **Chapter 4** we report results from a winter field study, carried out at the University of Bath campus, that used in-depth energy, environmental and motion sensing to generate real-time context-aware feedback through a smartphone application. Drawing from the results of this study, we show that real-time feedback can contribute to an increase in occupant perceived environmental control, a key variable in the theory of adaptive thermal comfort, while making occupants more thermally satisfied. Feedback have also the ability to prompt lower heating energy behaviours. This finding provides new important insights on the future role of feedback and on the importance of perceived control in thermal comfort.

5.2 Recommendations for further work

Additional studies will be needed to further address **R**esearch **Q**uestion **1** and understand how feedback will impact the adaptive responses of both residential and office occupants. This is a complex and fascinating topic which will become more relevant in the future with the expected roll-out of smart meters around the world.

Within the Smart Controls and Thermal Comfort (SCATs) EU Project, comprehensive monitoring data and year-round surveys of 26 European buildings were collected. This dataset represents a great opportunity to apply and extend the methods developed in this thesis, as it would help to further address the **R**esearch **Q**uestions **2** and **3** within the European region.

Bibliography

ASHRAE, 2013. *Standard 55:2013 – Thermal Environmental Conditions for Human Occupancy (ANSI Approved)*. American Society of Heating, Refrigerating and Air-Conditioning Engineers.

Baker, N. and Standeven, M., 1996. Thermal comfort for free-running buildings. *Energy and Buildings* 23 (3), pp. 175 – 182. DOI: 10.1016/0378-7788(95)00942-6.

Boerstra, A. C., Hoof, J. van, and Weele, A. M. van, 2015. A new hybrid thermal comfort guideline for the Netherlands: background and development. *Architectural Science Review* 58 (1), pp. 24 – 34. DOI: 10.1080/00038628.2014.971702.

Boerstra, A. and Brager, G., 2012. Personal control and Occupant behavior.

De Dear, R. J., Brager, G., Reardon, J., Nicol, F., et al., 1998. Developing an adaptive model of thermal comfort and preference/discussion. *ASHRAE transactions* 104, p. 145.

Dear, R. J. de, Akimoto, T., Arens, E. A., Brager, G., Candido, C., Cheong, K. W. D., Li, B., Nishihara, N., Sekhar, S. C., Tanabe, S., Toftum, J., Zhang, H., and Zhu, Y., 2013. Progress in thermal comfort research over the last twenty years. *Indoor Air* 23 (6), pp. 442 – 461. DOI: 10.1111/ina.12046.

EN, 2007. *EN 15251:2007 – Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics*. European Standard.

Fanger, P. O., 1970. *Thermal Comfort*. McGraw-Hill.

Gagge, A. P., Stolwijk, J. A. J., and Hardy, J. D., 1967. Comfort and thermal sensations and associated physiological responses at various ambient temperatures. *Environmental Research* 1 (1), pp. 1 – 20.

Halawa, E. and Hoof, J. van, 2012. The adaptive approach to thermal comfort: A critical overview. *Energy and Buildings* 51, pp. 101 – 110. DOI: 10.1016/j.enbuild.2012.04.011.

Havenith, G., Holmér, I., and Parsons, K., 2002. Personal factors in thermal comfort assessment: clothing properties and metabolic heat production. *Energy and Buildings* 34 (6). Special Issue on Thermal Comfort Standards, pp. 581 – 591. DOI: 10.1016/S0378-7788(02)00008-7.

Humphreys, M. A., 1976. Field studies of thermal comfort compared and applied. *Build Serv Eng* 44 (1), pp. 5 – 23.

Nicol, F. and Humphreys, M., 2010. Derivation of the adaptive equations for thermal comfort in free-running buildings in European standard EN15251. *Building and Environment*

45 (1). International Symposium on the Interaction between Human and Building Environment Special Issue Section, pp. 11 – 17. DOI: 10.1016/j.buildenv.2008.12.013.

Nicol, J. F. and Humphreys, M. A., 1973. Thermal comfort as part of a self-regulating system. *Building Research and Practice* 1 (3), pp. 174 – 179. DOI: 10.1080/09613217308550237.

Nicol, J. F. and Humphreys, M. A., 2002. Adaptive thermal comfort and sustainable thermal standards for buildings. *Energy and Buildings* 34 (6). Special Issue on Thermal Comfort Standards, pp. 563 – 572. DOI: 10.1016/S0378-7788(02)00006-3.

Parsons, K., 2002. *Human Thermal Environments: The Effects of Hot, Moderate, and Cold Environments on Human Health, Comfort and Performance, Second Edition*. Taylor & Francis.

Schweiker, M., Fuchs, X., Becker, S., Shukuya, M., Dovjak, M., Hawighorst, M., and Kolarik, J., 2017. Challenging the assumptions for thermal sensation scales. *Building Research and Information* 45 (5), pp. 572 – 589. DOI: 10.1080/09613218.2016.1183185.

Van Hoof, J., 2008. Forty years of Fanger's model of thermal comfort: comfort for all? *Indoor Air* 18 (3), pp. 182 – 201. DOI: 10.1111/j.1600-0668.2007.00516.x.

Appendix

This appendix reports on three supporting studies that are each based on a journal paper, and where the author of this thesis contributed to ideas and analyses.

In the first study, we report a field study of thermal comfort in desert refugees camps in both the summer and winter seasons.

In the second study, a new probabilistic adaptive comfort theory is introduced. This theory provides new comfort equations for resilient building design.

In the third study, indoor thermal comfort is investigated in three different free-running offices (naturally ventilated, mechanical ventilated and mixed-mode) in Colombia.

The three studies contribute to the knowledge on adaptive thermal comfort. The analysis are mostly carried out by the author of this thesis using the programming language Python. The exact contribution for each article is specified in the declaration of authorship preceding each article.

Thermal comfort in desert refugee camps

This research forms part of the project HHftD (Healthy housing for the Displaced) funded by the EPSRC. The project aims at improving the living conditions in refugee camps by designing low cost and easy to construct housing that will moderate extremes of temperature and ensure the privacy, comfort and dignity of residents. The work presented in this section reports the results of the very first monitoring campaign carried out in two Syrian refugee camps in Jordan, during both the summer and winter seasons.

This represents the first such work with this understudied population of refugees living in camps. A new approach for conducting thermal comfort surveys in foreign languages is presented. This approach could be used in other languages were literal translation from English could not be used. By analysing the collected thermal comfort data, a comfort temperature band for the refugees is estimated to be between 17.2 and 28.5°C, suggesting a significant adaptability of the refugees, but not one equal to the large temperature range found on site. Fanger's PMV/PPD model is found to underestimate the adaptive potential of the refugees, while the comfort temperature bands calculated for each season fit well within the ASHRAE adaptive comfort bands suggesting the this model is able to predict thermal comfort in the monitored camps.

This work is totally based on a same-titled paper published in Building and Environment in 2017, more details are provided below.

Appendix

Declaration of Authorship

This declaration concerns the article entitled: Thermal comfort in desert refugee camps: An interdisciplinary approach	
Status	Published in Building and Environment.
Details	Dima Albadra, **Marika Vellei**, David Coley, & Jason Hart, Thermal comfort in desert refugee camps, Building and Environment, 2017, Volume 124, Pages 460-477. DOI: doi.org/10.1016/j.buildenv.2017.08.016
Authors' contribution	The author of this thesis contributed to designing the questionnaires and defining the methodology (20%) and to carrying out the thermal comfort analysis (100%) reported in Section 5.3 and 5.4. Each author's exact contribution to the article is outlined below: D. Albadra: Formulation of ideas (80%), Design of methodology (70%), Collection of data (100%), Processing/Analysis of data from social surveys (100%), Preparation of the manuscript (70%). **M. Vellei**: Formulation of ideas (10%), Design of methodology (20%), Processing/Analysis of thermal comfort data (100%), Preparation of the manuscript (20%). D. Coley & J. Hart: Formulation of ideas (10%), Design of methodology (10%), Editing drafts of manuscript (10%).
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.
Date and Signature	

Thermal comfort in desert refugee camps

D. Albadra, M. Vellei, D. Coley, J. Hart*
Department of Architecture and Civil engineering, University of Bath, UK
*Department of Social and Policy Sciences, University of Bath, UK

Abstract

Long-term encampment is a growing aspect of a growing refugee crisis. There is hence the need to ensure shelters provide a safe and suitable environment. We present the first field study including social and thermal comfort surveys and physical measurements conducted in Syrian refugee camps in Jordan, during summer and winter. This required the creation of a new Arabic thermal comfort survey based on the numerical ASHRAE scales to ensure the elimination of any ambiguities due to translating the scales. The three analysis methods used (linear, logistic and multiple logistic regression) all gave the same neutral temperature, 23°C; however, Fanger's predicted mean vote model was found to underestimate the adaptive potential of the refugees. The comfort band found using logistic regression ranged from 28.4°C to 17.2°C, suggesting a significant adaptability of the refugees, but not one equal to the temperature range found on site. Issues with the clash between ventilation, privacy, security and sand ingress were identified, and this points to a need to re-evaluate shelter ventilation in general. However, given the extreme conditions recorded, natural cross ventilation alone will not be sufficient in achieving summer comfort. Combining this with the observation that, due to safety and lack of resource, the refugees have no means of heating at night, a shelter solution that successfully includes insulation, and possibly thermal mass would seem important.

Keywords

Thermal comfort, Refugee camps, Arabic survey, Field study, Jordan

Abbreviations

TSV thermal sensation vote
TPV thermal preference vote
PMV predicted mean vote

Nomenclature

T_n Neutral temperature
T_o Operative temperature
I_{cl} Clothing insulation
V_a Air velocity
T_a Air temperature
T_g Globe temperature

1. Introduction

According to the United Nations Refugees Agency UNHCR, we are currently witnessing the worst refugee crisis recorded [1]. As of the end of 2014 there were over eight million people living in encampments as a result of armed conflicts [2]. In addition, over nineteen million new people were displaced due to natural hazards in 2015 alone [3]. These are not short term displacements: at the end of 2014 there were people living in conditions of internal displacement for over ten years in nearly 90% of the sixty monitored countries [4]. Similarly, major refugee situations last nearly two decades on average [5].

In comparison to issues such as food, water and medical care, shelter design and performance is understudied and rarely evaluated, despite it being known that prolonged exposure to extreme thermal conditions can lead to morbidity and mortality [6]. The shelters provided by humanitarian agencies are generally lightweight structures and are ineffective against high summer temperatures, or winters where temperatures can plunge well below freezing. The struggle to cope with such adverse conditions only adds to the psychological burden of people coming to terms with the loss of loved ones, community and property. In order to inform future shelter design, it is therefore important to understand both the current conditions in such camps and the thermal comfort limits and preferences of the targeted population.

In this paper we assess for the first time thermal comfort in desert refugee camps via social and thermal comfort surveys, and physical measurements. The objectives of this paper are to: 1) assess the environmental conditions, 2) discover common thermal adaptation methods, 3) assess priorities and needs in terms of shelter design, 4) evaluate the refugees' thermal preferences, comfort limits and establish their neutral temperature. In addition, we develop and test a new approach to the ASHRAE comfort scales designed specifically for translation into any language, including use with illiterate populations, and publish the first comfort survey in Arabic.

2. Adaptive thermal comfort theory

Two approaches to human thermal comfort have evolved over the past half a century. The steady state approach, pioneered by Fanger in the late 1960s [7]; and the adaptive approach introduced by Nicol and Humphreys in the 1970s [8]. Both allow the thermal environment experienced by a population to be measured by asking occupants to score their environment (a process termed voting) on the same 7-point *thermal sensation* scale (from cold to hot). The steady state approach assumes that any degree of thermal stress, and consequently any effort to adjust to it, is undesirable [9]. Thus, Fanger developed an index to predict the mean *thermal sensation* vote of a population based on the heat balance of the human body, and termed this the Predicted Mean Vote (PMV) [7]. This index was derived through research in climate chambers and resulted in a defined narrow thermal comfort zone that served the needs of the air-conditioning industry and was therefore mainly intended for application in conditioned spaces. On the other hand, the adaptive approach considers physiological (acclimatisation), behavioural (adjustment) and psychological adaptation (habituation and expectation) [10]. It demonstrated through field surveys that people living in naturally ventilated buildings were satisfied at a much wider range of temperatures than those found in conditioned buildings [10] [11]. The approach did not aim to determine an optimum set of indoor environmental variables but rather to define a band of temperature within which an occupant can find his or her own optimum given sufficient adaptive opportunities, for example removing a jacket, or opening a window. A key feature of the approach is that it predicts that the temperature people are comfortable at (termed the comfort or neutral temperature) is a function of the outdoor air temperature over recent days [12].

Assessing thermal comfort through field studies where occupants are questioned about their comfort is now a common practice across the world, for example, in: Japan [13], Malaysia [14], Nepal [15], UK [16], Australia [17], the USA [18], India [19], Libya [20], Tunisia [21], and Iran [22]. Indeed the ASHRAE-55-2004 to 2013 [23] adaptive thermal comfort standards are based on results obtained through field comfort surveys. However, no robust research on thermal comfort has been carried out in refugee camps that are composed of temporary shelters—which can end up being inhabited for decades. Such camps tend to be placed in inhospitable environments with extreme climatic conditions. Their inhabitants are displaced, invariably foreign to the camp's location/climate, and its accommodation. A recent study [24] demonstrated that it is hard for migrating populations to adapt to environments that are less thermally comfortable or of lesser quality than their long term thermal history.

3. The surveyed camps

The two camps studied are sited in northern Jordan in a desert hot and dry climate [25]. Since 2011 the Syrian crisis has resulted in a mass displacement of people, and Jordan currently hosts 664,100 Syrian refugees: around 80,000 of those are housed in the Zaatari camp and 54,000 in the Azraq camp [26]. In Zaatari the mean maximum outdoor temperature is 32.7°C and the mean minimum is 1.9°C. In Azraq the mean maximum outdoor temperature is 36°C and the mean minimum is 2.8°C [27].

Zaatari (32.29° N, 36.33° E) consists of caravan-like structures (which replaced tents). 11% of these are static caravans with screed flooring with the walls and roofs made of 40mm polyurethane insulated sandwich panel with inner and outer surfaces of 0.35mm steel sheet (G. Barakat, personal communication). The remaining 'mobile' caravans are also made of insulated sandwich panels, however they sometimes have timber inner surfaces and a suspended timber floor, which in some cases has been replaced by the refugees with a screed of cement mortar over rubble (Figure 1, right). None of the designs were developed after completing a survey of the physical or social preferences of the population; hence, for example, low level windows allow passing males to see into female areas. This means windows become occluded, reducing ventilation rates. However, unlike Azraq, occupants and caravans can relocate to ensure occupants are in a neighbourhood in which they have family.

Azraq camp (31.91° N, 36.59° E) was pre-planned, and 13,500 shelters were built of corrugated metal sheeting separated by 10mm of foam-based insulation (Figure 1, left). Picking up on some of the lessons learnt at Zaatari, the shelters were designed "to maximise privacy and protect against severe weather conditions” [28]. The need for privacy led to a design with only one window and high level openings consisting of short lengths of 152mm waste pipes on the gables, thereby restricting the ability to cross ventilate. In addition, the design drawings show numerous cold bridges with the potential to form points of condensation, and thermal by-pass due to loose insulation This has probably resulted in a significant failing of the design; a qualitative assessment of the Azraq camp conducted by REACH in 2015 confirms this, as it was found that 90.2% of 600 respondents were unsatisfied or very unsatisfied by the temperature in their shelters in summer and 44.8% were unsatisfied or very unsatisfied by the temperature in their shelters in winter [29].

Figure 1: Azraq camp (left) notice the camp follows a grid layout, Zaatari camp (right) caravans are randomly arranged as suits the refugees. (Photo: S.Coley.)

4. Methodology

A thermal comfort survey, including spot measurements of environmental parameters, was conducted directly in a Levantine Arabic dialect similar to that spoken by the refugees. In addition, a social survey was conducted to record the views of refugee families on shelter design, adaptation methods, satisfaction and preferences. The surveys were completed in late summer (31^{st} of August to 23^{rd} of September 2016) and winter (2^{nd} to 22^{nd} of January 2017) between 9:30am and 3:00pm.

4.1 Data collection

The families were selected randomly. Given the range of backgrounds, intra-household dynamics, education and literacy levels, all surveys were administered through interview. The questions were explained in detail in order to guarantee common understanding amongst occupants. The summer survey consisted of 75 families (38 families in Azraq and 37 families in Zaatari). Fifty-six of the 75 families were visited again for the winter survey, and an additional 24 families were interviewed in winter to compensate for those who were not available. The respondents were interviewed in their residence (shelters). First, the respondents as a family unit were asked to answer the social survey questionnaire; all family members present discussed the questions and one response per family per season was recorded as the main interest of the social survey was to find out, what aspects of the shelter design worked (or didn’t) for them as a family. This took about twenty minutes allowing them to physically acclimatise in case they were doing other activities prior to the survey. Then they were asked individually about their thermal sensation and thermal preference while spot measurements of indoor environmental variables were recorded using hand-held devices at 1m high. Respondents' height, weight, age, clothing level, and activity level, were noted.

A weather station was established in Zaatari during the summer survey and in Zaatari and Azraq during the winter survey. The weather station in both locations was set up on a tripod 2.5m high on the roof of UNHCR office caravan located within the camps. The sample period of air temperature, relative humidity (RH) and global solar radiation onto the horizontal measurement was one minute with averages recorded every 30 minutes. Wind speed and direction were recorded at one minute intervals. (see table A1 in appendix A for details of the instrumentation).

4.1.1 Sampling method for the thermal comfort survey

There are two common sampling methods when conducting thermal comfort surveys, transverse and longitudinal. In the former, large numbers of individuals are used, with the survey being completed once. In the latter, which is more common, a smaller sample are repeatedly surveyed over a long period of time in order to cover a large range of temperatures. Ensuring a large range in air temperature is known to be important in such work [30]. The number of data points (responses) collected varies significantly in the literature. For example, Luo et al., [31] obtained 834 points from 50 individuals, Sharma and Ali [32] obtained a total of 5100 from 18 individuals, Mustapa el al, [33], collected 303 from 28 individuals and Indraganti and Rao [34] collected 3962 responses from 100 individuals. In a transverse survey, Ogbonna and Harris, [35] had a sample size of 200 subjects, Feriadi and Wong, [36] had 525 subjects.

In this study, due to security restrictions and the nature of the survey that mandated interviewing the individuals, a repeated transverse survey was used. In total 336 datasets were collected over the summer and winter from 270 individuals from 99 households across both camps, and a range of indoor air temperatures from 12°C to 37°C was achieved.

4.1.2 Scales and terminology

The thermal comfort scales were the standard 7-point ASHRAE *thermal sensation scale* and the 5-point *thermal preference scale*. The thermal sensation scale records an occupant's Thermal Sensation Vote (TSV) on a scale of (hot to cold), while the thermal preference scale asks the occupant what their preferred sensation is (Thermal Preference Vote, TPV) at that moment, from much cooler to much warmer. The ASHRAE scales uses the terminology 'neutral', 'slightly warm', 'warm', 'hot', 'slightly cool', 'cool', and 'cold' for TSV, and 'no change', 'a bit cooler', 'much cooler', 'a bit warmer' and 'much warmer' for TPV. The word 'warm' in standard Arabic and Levantine Arabic dialect - *dafi* - has a positive meaning, i.e. to be warm is a positive sensation and is never used in a summer context. In a winter context, being warm is understood as being comfortable. To imply a negative warm sensation, the equivalent of the word 'hot' is used, i.e. (*moshaweb*) On the other hand, there is no equivalent to the word 'cool' in Arabic, only 'cold', (*barred)*, which is a negative sensation. This was especially problematic as demonstrated during a pilot of two families in Azraq in the hot season when respondents were asked whether they preferred their environment to be 'a bit' or 'much colder' in Arabic as opposed to the English 'a bit or much cooler'. The respondents were confused and gave answers along the lines of "I prefer the weather to be nicer but not cold as in winter". Studies in Japan [37] and Nepal [15] highlighted similar issues when conducting a thermal comfort survey using local languages. In this study, in order to address such issues, the respondents were first asked whether they felt absolutely neutral (*hiyadi*) or felt a sensation of heat or cold. If they answered neutral, (*hiyadi*), their thermal sensation was registered as such. If they said they felt a discomfort or sensation of heat or cold, then they were asked to say on a scale 1 to 3 how hot or cold they felt with 1 being a little bit, and 3 being too much. A similar numerical approach was used for the thermal preference scale.

4.2 Calculation of indices

4.2.1 Operative temperature

The expression of comfort by an individual is related to the operative temperature (which is a combination of the air and radiant temperatures and the air speed). Using the recorded measurements of air temperature, globe temperature and air speed, the operative temperature was calculated using equation (1) provided in ISO 7726 [38]:

$$T_o = \frac{T_r + (T_a . \sqrt{10V})}{1 + \sqrt{10V}} \tag{1}$$

where T_r is the mean radiant temperature, T_a the air temperature and V the air speed. The measured globe temperature T_g was used to represent the mean radiant temperature (T_r) as suggested by Nicol et al., [39], given the likely error in measuring T_r.

4.2.2 Metabolic rate and clothing insulation

Metabolic rate was estimated using tables available in ASHRAE 55, based on the subject's activity observed during the 15 minutes prior to the start of the questionnaire. Total clothing insulation values I_{cl} are expressed in clo units. The ASHRAE 55 and ISO 9920 standards [40] include tables of insulation values for common clothing ensembles in the western world, but more recently values for Asian and Middle Eastern communities were proposed in [41], [42]. Although the refugees clothing shared a few characteristics with these gulf and Middle Eastern ensembles, for example the Hijab or headscarf, other aspects of the ensembles were significantly different. For example, in summer, the majority of men wore western style trousers and t-shirts, while a few wore traditional head wear, with either western clothes or the traditional long dresses, see Figure 3, as opposed to the thinner headwear and white dress suggested in [41]. Women on the other hand, wore a headscarf and floor length, long sleeved, coloured dresses, and underneath wore a pair of pyjamas, leggings or thin cotton trousers. In winter, both males and females wore several layers of clothing when inside their shelters, including jackets (Figure 2). In order to calculate the most representative clothing insulation values, in most cases the closest ensemble available was used, mainly those provided in [42], and then the value of available garments insulation was subtracted or added to it as shown in Table 1.

Table 1: Examples of refugee clothing insulation.

	Al Ajami et al., 2008 'islamic dress'		Calculated refugee clothing (minimum values)	
	ensemble	I_{cl} (clo)	ensemble	I_{cl} (clo)
Women Summer	Bra, pants, sandals, long dress, hijab	0.8	Bra, pants, long bottoms, long dress, hijab, barefoot	0.93
Women Winter	Bra, pants, shoes, socks, thicker dress, hijab	1.15	Bra, pants, long bottoms, long sleeve blouse, thicker dress	1.43
Men Summer	T-shirt, short bottoms, long dress, sandals, headwear	0.69	Men western style clothing: Men briefs, t-shirt, short sleeve blouse, trousers	0.43
Men Winter	T-shirt, short bottoms, long serwal (bottoms), long dress, socks, shoes, headwear	0.79	Men western style clothing: Men briefs, t-shirt, long sleeve sweater, thick trousers, socks	0.75

Figure 2: Examples of indoor winter clothing. It is clear that occupants wore several layers to keep warm. (Photo: S. Coley)

Figure 3: Examples of indoor summer clothing. Men had a greater flexibility than women in adapting their clothing between seasons.

4.2.3 The predicted mean vote model

The adaptive comfort model uses a questionnaire to obtain the occupants' actual thermal sensation votes while recording indoor environmental variables. By contrast, the Predicted Mean Vote (PMV) model developed by Fanger predicts an occupant sensation vote based on the heat balance of the human body taking into account indoor environmental variables and the influence of clothing and metabolic rate [43]:

$$\mathrm{PMV} = (0.303\,\mathrm{e}^{-0.036\mathrm{M}} + 0.028)\,\mathrm{L} \qquad (2)$$

where M is metabolic rate and L the thermal load. (This is defined as the difference between the internal heat production and the heat loss to the actual environment.)

The PMV of each individual was calculated using a visual basic routine [44] based on guidance and equations available in ISO-7730 [43].

4.3 Regression methods

Given that the votes and spot measurements of the environmental variables in the dwellings were recorded simultaneously, regression can be used to estimate the temperature at which a population will feel neutral and the range of temperatures the majority (80%) are likely to feel comfortable over. Simple and multiple linear regressions are the most widely used methods for modelling occupant thermal sensation in field studies [10, 11, 13, 19, 33, 45-52]. In our case, the simple linear regression method consists of plotting the TSV recorded from the refugees against the indoor operative temperature (T_o) and drawing the regression line; the neutral temperature (T_n) is then the temperature corresponding to a mean TSV of zero [29]:

$$\text{TSV} = a\,\text{T}_\text{o} + b \tag{3}$$

and

$$\text{T}_\text{n} = -b/a\,. \tag{4}$$

The surveyed data was collated into 1°C intervals before the regression was completed, in line with [10].

The gradient, α, of the linear regression indicates the temperature perturbation needed for a change of 1 unit in TSV. It is therefore a measure of occupant sensitivity to indoor temperature changes and gives the degree to which a population is able to adapt to changes in the thermal environment. Less steep gradients are indicative of a larger range of temperatures (termed the comfort band) over which occupants consider themselves to be comfortable, and can be associated with more effectively adapted and less sensitive occupants who are able to tolerate exposure to a wider range of indoor operative temperatures [19] [53].

Similarly, T_n can be obtained through a simple linear regression using the TPVs of the whole population instead of the TSVs. This is known as the preferred neutral temperature and it is sometimes argued that it is a more appropriate indication of the optimum comfort temperature [10].

However, there are some statistical issues in the use of linear regression in thermal comfort research. Such issues arise from modelling an ordinal response, such as TSV, using a continuous model [54] in addition to the extreme simplicity of the linear model. Hence, several works propose logistic regression as an alternative [55]. Multinominal logistic regression [56] predicts the probability of a dependent variable, in our case TSV or TPV, which can take more than two values, given the value of a predictor variable, in our case T_o:

$$ln\left(\frac{P(TSV)}{1-P(TSV)}\right) = \beta_0 + \beta_1 T_o \tag{5}$$

and similarly for $P(TSV)$. Equation (5) is,

$$P(TSV) = \frac{e^{\beta_0+\beta_1 T_o}}{1+e^{\beta_0+\beta_1 T_o}} \tag{6}$$

In this case, the neutral temperature can be interpreted as the temperature corresponding to the highest probability of having a neutral TSV (i.e. a TSV between -1 and 1).

Both the linear and logistic regression assume that the only variable with influence over TSV is the operative temperature. Given other variables were included in the measurements made in the shelters and of the occupants, it is natural to ask if any of these influenced the thermal sensation or thermal preference votes of the refugees, and if so, by how much. Multiple logistic regression expands equation (5) to include K potential influences X_1 to X_K:

$$ln\left(\frac{P(TSV)}{1-P(TSV)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_K X_K \quad (7)$$

Examples of influences would be the air temperature, the relative humidity and the clothing level of the refugees.

We use all three forms of regression to analyse the data from the thermal comfort surveys in the camps. The Mann–Whitney U test is used to compare differences between samples and the significance level is 0.05.

5. Results and discussion

5.1 Social survey

The average number of members per household was 6.2. It was found that 87% of respondents had adapted their shelter (Figure 4 a, b). The most common adaptations to the shelters were expanding the shelter by lightweight structures such as fabric or metal sheeting. Over 35% of families cut an additional window in Azraq while less than 5% did the same in Zaatari. Moreover, it was observed that the high-level pipe openings provided for ventilation in Azraq shelters tended to blocked by residents to eliminate sand ingress in summer and cold draughts in winter. Provision of security and safety was cited as the most important aspect in the design of a shelter, followed by thermal comfort then privacy (Figure 5). In Azraq, which suffers from harsher summers, the provision of thermal comfort was cited by 22% of respondents as the most important aspect in shelter design, and as the second most important by 44%, compared to 25% and 28% respectively in Zaatari. In addition, families were asked to rank their satisfaction with certain aspects of their shelter from (1) to (5) with (1) being very unsatisfied and (5) being very satisfied. The majority of families reported that they found their shelters to be unbearably hot in July and August, while they also found it freezing in winters especially at nights. Overall, 85% of the families were unsatisfied or very unsatisfied with the thermal conditions in summer while only 33% said the same in winter (Figure 6). However, in Azraq 100% of families said they were unsatisfied or very unsatisfied with the thermal conditions in summer compared to 18% in winter. While in Zaatari, the percentage of unsatisfied/very unsatisfied families in winter was 48% compared to 73% in summer. With regards to safety/security, 75% of the families were satisfied or very satisfied with the safety of their shelters.

(a)

(b)

Figure 4: (a) Zaatari: caravans adapted by covering the area between the shelters and pouring a concrete floor in the interior covered court-yard. (b) Azraq: adaptation by enclosing the outside and adding an interior layer of aluminium foam insulation.

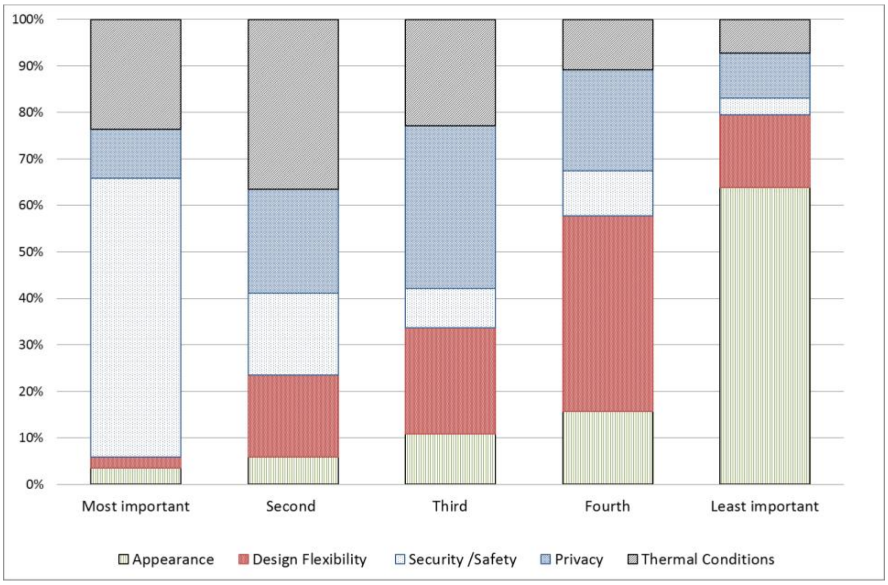


Figure 5: Ranking of design considerations from the social survey; several families were only able to point out their first two priorities and were not able to rank their remaining preferences.

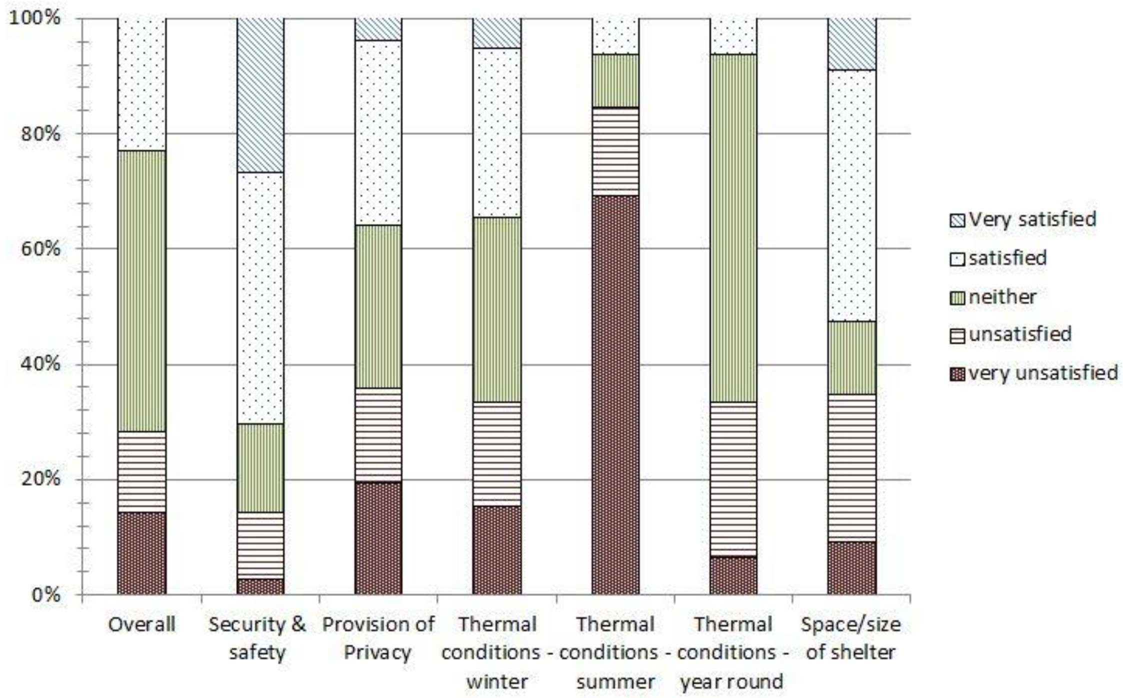


Figure 6: Satisfaction with basic shelter parameters from the social survey.

5.2 Thermal adaptation

In both the summer and winter surveys, families were asked about their thermal adaptation strategies. No options were given; instead the families just reported in freeform what they did to cope with the heat or cold.

5.2.1 Summer

The most reported coping mechanism in summer was to shower or pour water onto themselves with their clothes on, repeatedly throughout the day (Figure 7). The second most common strategy was using wet towels wrapped around their head, neck or shoulders in Zaatari and spraying the screed floors with water in Azraq. Removing carpets and sitting on the screed floor was frequently reported in Azraq, while many families in Zaatari reported sitting in the covered courtyards with screed flooring that the occupants had created between their caravans. 79% of the families kept the windows open all the time, with “dust” and “sandstorms” being the most common reason for closing windows – 61% of the time, other reasons included security and privacy (19%), feeling cold at night (13%) and bugs (7%). 50% of the families in Azraq reported having limited ability to adapt their clothing, especially women as they kept doors and windows open, while only 35% felt the same in Zaatari, this is mainly because Zaatari residents had more freedom in adapting their shelters, changing the orientation of the caravans and building extensions to create a more private space while still allowing ventilation.

5.2.2 Winter

Over 90% of the families used a gas heater as the main method of keeping warm (Figure 8). The heater was reportedly kept on for an average of 10 hours a day. In addition to using a gas heater, using blankets was cited by 40% of the families as a winter strategy; and covering the floor with a carpet by 33%. The coolth of the concrete flooring, which was desired in summer, was frequently reported as a source of discomfort in winter. Other sources of discomfort cited were gaps and draughts around the structure (68%), and the type of building materials used in the shelters (55%). Several considered the inability to use the gas heater at night due to safety concerns, or during the day due to lack of fuel, as a main reason for discomfort (18%). Families were asked whether they ventilated frequently during winter: 23% responded yes, 64% reported that they were only doing so during the day while it was sunny outside. 22% said that they maintained background ventilation by not blocking ventilation pipes or gaps in the structure, or opening an interior door/window onto a self-built and therefore draughty extension.

Some of the families had savings, work permits or were receiving help from relatives, which meant they had access to more means of adaptation, for example, buying insulation boards and additional gas cylinders. It was observed that most refugees wore many layers of clothing when indoors in winter despite this being reported as an adaptation strategy by only 15% (in Figure 8). Moreover, when asked about their movement throughout the day, it was found that on average 50% and 28% of families spent their time in semi-outdoor spaces such as shaded courtyards and enclosed external spaces; in summer and winter respectively (Figure 9); although this was reported as a thermal adaptation strategy in summer by only 18% (Figure 7).

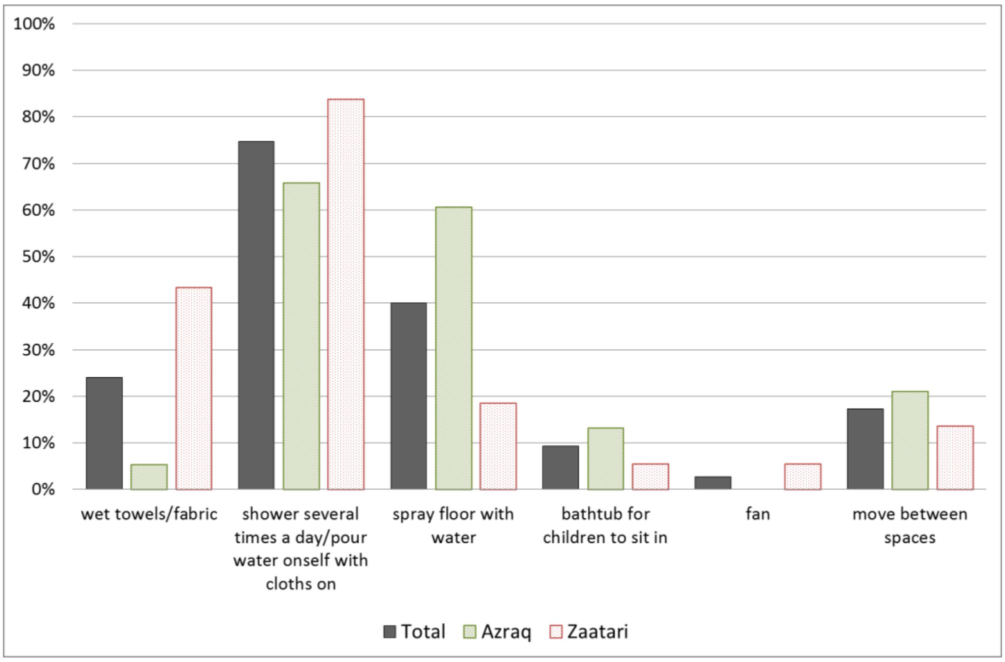


Figure 7: Thermal adaptation methods in summer. 'Total' refers to both camps combined. Showering in this case was reported as a cooling strategy, not for hygiene, and takes place with clothes on.

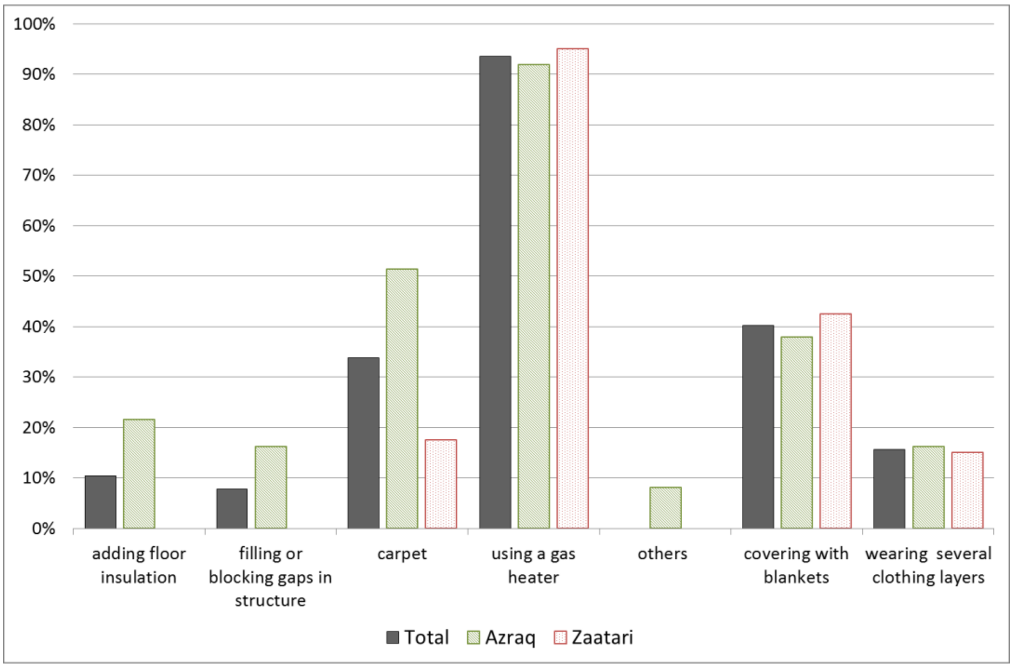


Figure 8: Thermal adaptation methods in winter, 'others' includes drinking hot drinks, sitting in the sun.

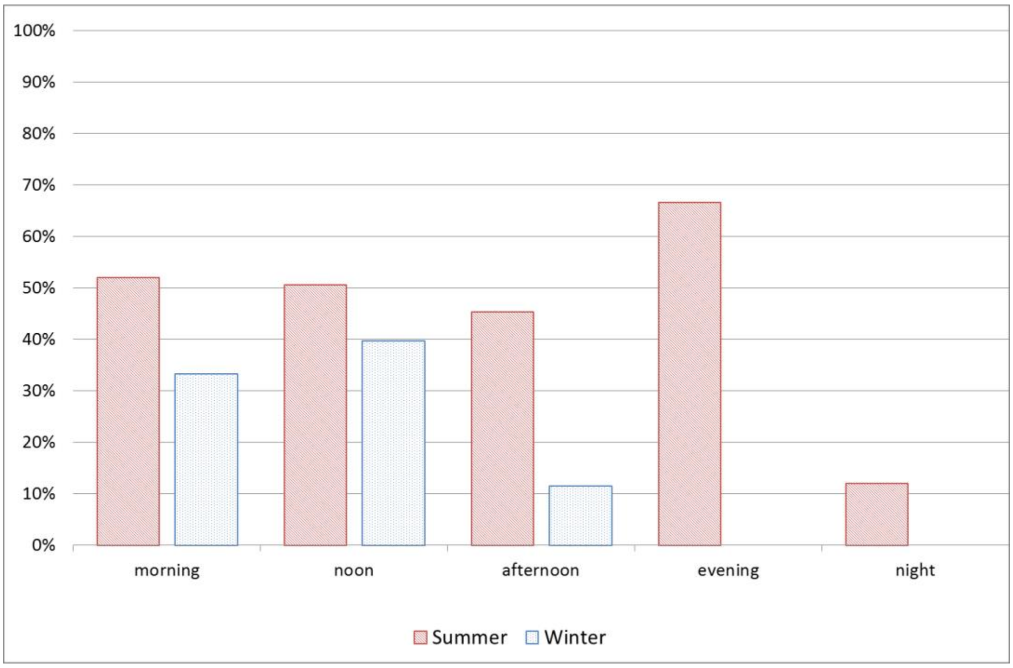


Figure 9: Time spent in the semi-outdoor spaces of the shelters; the question asked was "when at home, where do you spend your time in the morning/noon/afternoon/evening/night?"

5.3 Thermal comfort survey

In total 336 surveys were completed, 160 in summer and 176 in winter; 58% of respondents were female. The age of the respondents varied between 13 and 92 years; the mean and standard deviation (SD) was 34.6 ±14.11 years (Table 2). In summer, the mean TSV was 1.4 for the total population of Azraq and Zaatari, which is on the warm side of the ASHRAE thermal comfort scale. In winter, the mean TSV for the total population was -0.5 which is close to neutral (0), indicating higher thermal satisfaction in winter than in summer. This could be due to the fact that the surveys were conducted during the day (9:30-15:00) when outdoor temperatures in winter were more modest, or it might be due to the greater potential for clothing adaptation in winter discussed later. All the parameters reported in Table 2, 3 and 4 are approximately normally distributed [57], except for the air speed which shows a strong positively skewed distribution, and hence its standard deviation (SD) is not useful in describing the data.

Table 2: Characteristics of male and female respondents. Data are mean ±SD.

		No. Subject		Age (years)		Height (cm)		Weight (kg)	
		M	F	M	F	M	F	M	F
Azraq	Summer	43	41	35.4±11.6	33.5±13.7	171.9±7.5	159.8±4.3	75.4±13.7	66.0±12.1
	Winter	33	56	39.1±14.7	35.8±13.9	174.2±8.3	160.8±7.2	74.8±14.7	71.8±17.2
Zaatari	Summer	33	43	31.8±13.5	32.1±14.9	169.9±9.1	161.0±6.6	69.1±12.5	68.8±14.7
	Winter	32	55	35.2±16.6	34.0±14.3	171.3±8.9	159.3±5.0	77.7±13.3	75.3±15.6

Table 3: Thermal votes and clothing insulation values for males and females in both camps and seasons. Data are mean ±SD.

		TSV		TPV		Clothing (clo)	
		M	F	M	F	M	F
Azraq	Summer	1.5±1.2	1.6±1.3	-1.4±0.7	-1.5±0.6	0.50±0.07	0.93±0.05
	Winter	-0.1±0.8	-0.4±0.8	0.5±0.7	0.6±0.7	1.20±0.21	1.54±0.27
Zaatari	Summer	0.7±1.1	1.5±1.2	-1.0±0.7	-1.3±0.6	0.47±0.06	0.93±0.08
	Winter	-0.5±0.9	-0.7±1.2	0.7±0.7	0.8±0.8	1.02±0.32	1.48±0.26

Table 4: Environmental parameters. Data are mean ±SD. The minimum indoor temperature recorded was 12°C and the maximum 37°C.

		Indoor RH (%)		Indoor Av (m/s)		Indoor To (°C)		Tout (°C)
		M	F	M	F	M	F	
Azraq	Summer	22.3±6.8	25.0±5.2	0.14	0.11	33.3±2.5	32.5±2.4	33.7±2.4
	Winter	42.7±7.4	38.8±8.6	0.00	0.00	18.9±1.9	19.5±2.2	13.0±2.3
Zaatari	Summer	38.4±6.0	37.5±6.8	0.19	0.21	31.2±2.3	30.8±2.2	31.5±3.2
	Winter	37.9±6.5	37.1±7.9	0.03	0.10	18.3±2.0	17.9±2.5	11.2±1.9

5.3.1 The relationship between thermal sensation and thermal preference

It is reasonable to expect that those who vote 'neutral' on the thermal sensation scale will vote 'no change' on the thermal preference scale. While those who feel cold/warm will prefer a change in their environment. For example, a study in a naturally ventilated office building in China found that the vast majority of occupants (95%) who voted 'neutral' preferred 'no change' [31]. On the other hand, several studies have highlighted that votes on the thermal sensation and thermal preference scale may not be consistent. Indraganti et al., [58] found a preference for cooler indoor environments in southern India regardless of occupant thermal sensation votes. In hot and humid climates, Damiati et al., [59] found that 19% of those who voted neutral preferred a cooler temperature. In this study we found that in winter, there was a prevalence of 'no change' preference votes when the votes on the thermal sensation scale were on the warm side (1 to 3); while in summer 100% of those who felt 'slightly cool' preferred no change (Figure 10). This supports the "semantic artefact hypothesis" [10] that people prefer warm thermal sensations in winter and cool ones in summer. Furthermore, 68% of the people who voted 'neutral' in summer reported a preference for 'a bit/much cooler' environment while in winter 34% of the 'neutral' people preferred it to be 'a bit warmer'. This could indicate that refugees tolerate and thus adapt to their environment because they are unable to change it, but given the means they would prefer to 'improve' it. This was reinforced in the comments of the refugees where they have reported that they had come to accept their loss, and throughout the interviews, they repeatedly stressed that they were "grateful to be alive" or for having "a safe place" whenever asked about their satisfaction and preferences.

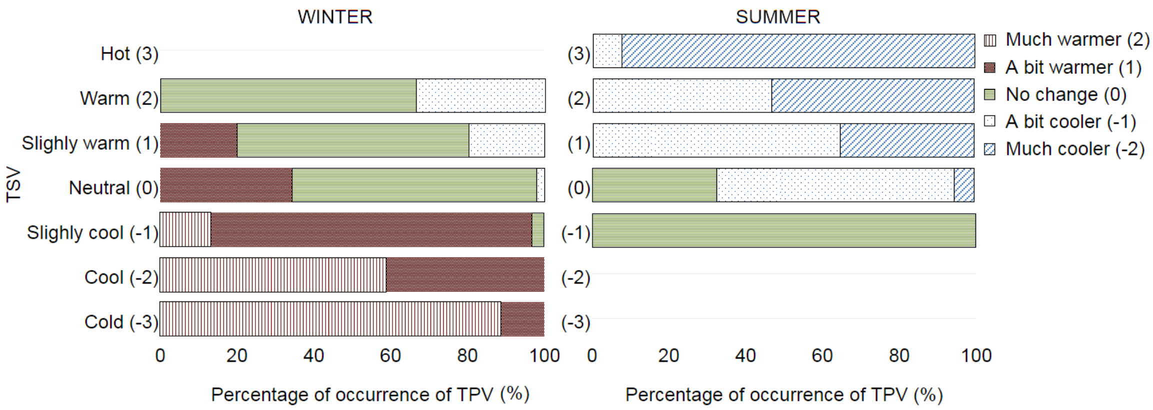


Figure 10: Distribution of TPV expressed as a percentage (%) for the different TSV in both seasons.

Figure 11 shows the cumulative percentage of wanting to be cooler (-1 and -2) and wanting to be warmer (1 and 2) against the thermal sensation scale. Both lines intersect at the neutral point. In a study by Indraganti et al., [13] they found that the "wanting to be cooler" and "wanting to be warmer" curves did not intersect at the neutral point, and the reasons given to justify the shift toward the cool side of the scale were either issues with the translation and the terminology used within the scale in Japanese, or because the survey was conducted only in summer. Humphreys et al., [45] note that translating the ASHRAE scale into different languages results in irregularities in the way it behaves, and that such irregularities are more attributable to the exact meaning of the words used rather than the actual thermal sensation.

Figure 11 accounts for both seasons, and therefore the fact that in this study the curves intersect at the neutral point is a powerful validation of our numerical approach to the questionnaire (explained in (4.1.2) and published in appendix B).

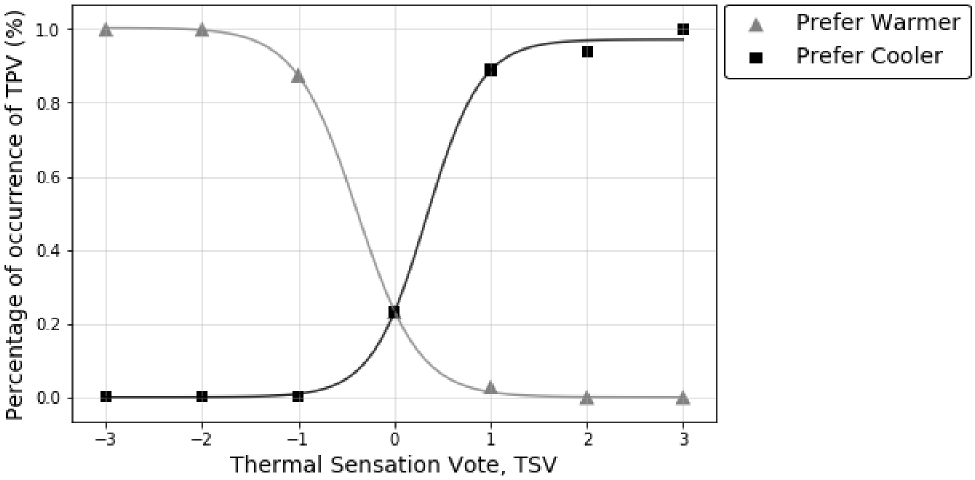


Figure 11: "Wanting to be cooler" and "wanting to be warmer" intersect at the neutral point on the thermal sensation scale. Logistic curves have been fitted to the data—with the data collated into 1°C bins.

5.3.2 The neutral temperature

We use simple linear regression (equation (4)) to derive the neutral temperature T_n for the whole population as explained in section 4.3. We use 1°C operative temperature intervals and discard intervals with only one vote. Tables 5,6 and 7 show the gradient (*α*) and intercept (*b*) of the fitted linear models together with the p-value for the gradient and the coefficient of determination (R^2). The p-value for the gradient tests the null hypothesis that the predictor (T_o) has no effect on the response variable (TSV), i.e. that the coefficient is equal to zero. A low p-value (<0.05) indicates that we can reject the null hypothesis. R^2 measures the proportion of variability in the response variable that can be explained using the predictor.

The thermal sensation and thermal preference regression lines (Figure 12) intersect with the neutral axis at almost exactly the same point and therefore give similar neutral temperatures (T_n): 22.7±0.75°C and 23.0±0.40°C, respectively (calculated value $\pm$ one standard error SE, Table 5).

According to the statistical assumption underlying Fanger's model [7], 80% thermal acceptability corresponds to a TSV between -0.85 and 0.85. This assumption is the same used in the adaptive comfort approach to define comfort bands for 80% acceptability using the TSV linear regression equation [10]. By substituting ±0.85 for TSV in the linear regression equation, the derived comfort temperature band for the whole surveyed population is seen to extend from 16.8°C to 28.5°C. The linear regression slope was 0.14/°C for the TSV of the whole population. This is a low angled slope; other studies in hot and dry climates [22, 48, 49] had a TSV gradient ranging from 0.13/°C to 0.25/°C. As explained earlier, less steep regression gradients indicate higher adaptability of the population.

Table 5. Linear regression.

	α	b	p-value	R^2	$T_n \pm SE$(°C)
TSV	0.1446	-3.2762	0.000	0.855	22.7±0.75
TPV	-0.1390	3.1958	0.000	0.951	23.0±0.40

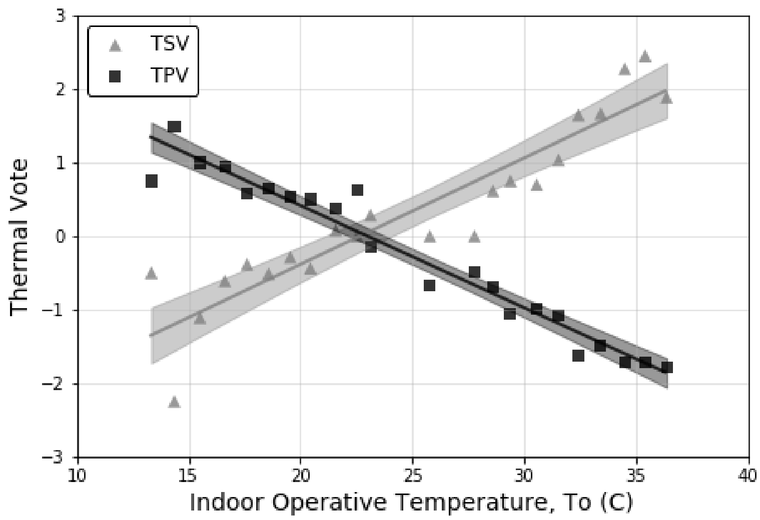


Figure 12: Linear regression models with 95% confidence bands.

5.3.3 Seasonal differences in the neutral temperature

Splitting the data into the summer and winter periods we find that in winter the gradient is less steep (Table 6), this means that people were more sensitive to changes in temperatures in summer and, therefore, summer is the season which posed more difficulties for their thermal adaptation. This might be expected, since in winter people had more means of adaptation (gas heating, clothing) than in summer (limited clothing adaptation opportunities for sociocultural reasons). The T_n calculated by using TSV for the summer season is about 5°C higher than in winter: 26.5±0.55°C and 21.8±1.30°C respectively. However, by using TPV we obtain very different results: 22.3±0.60°C in summer and 25.3±1.25°C in winter. While this could be explained by the above mentioned semantic artefact hypothesis, it should be noted that the difference we observe is much higher than the maximum 1.5K observed by De dear and Brager [10].

Table 6. Season-separated linear regression.

		α(/°C)	b	p-value	R^2	$T_n \pm SE$(°C)
TSV	Summer	0.2413	-6.4016	0.000	0.897	26.5±0.55
	Winter	0.1551	-3.3859	0.008	0.559	21.8±1.30
TPV	Summer	-0.1330	2.9707	0.000	0.886	22.3±0.60
	Winter	-0.0967	2.4511	0.005	0.609	25.3±1.25

5.3.4 Gender differences in the neutral temperature

Women were found to be slightly more sensitive (Table 7). This is in agreement with previous research [60, 46]. However, this was not necessarily only due to physiological differences but, in this particular context, could be attributable to differences in allowable clothing adaptation. However, in order to test if the two gradients of Table 7 are statistically significant, a multivariate linear model was computed for TSV having as predictors T_o, the gender and their interaction T_o*gender. The results of the model indicate that the interaction term is statistically significant ($p<0.05$), hence the coefficient of T_o depends on the gender.

Table 7. Gender-separated results of the linear regression analysis for TSV.

		α(/°C)	*b*	p-value	R^2	$T_n \pm SE$(°C)
TSV	Women	0.1584	-3.5150	0.000	0.892	22.2±0.85
	Men	0.1226	-2.7319	0.000	0.794	22.3±1.30

5.3.5 Predicted mean vote (PMV)

After calculating the PMV of each individual as described in 4.2.3, linear regression was then used to calculate the T_n and comfort bands based on the PMV. This allows us to compare it with the T_n calculated above using the actual TSV and check if the model is suitable for predicting the refugees' thermal sensation. A comparison between the predicted PMV and the actual TSV shows that the T_n(PMV) is 0.5K lower than T_n(TSV). However, the comfort band derived for ±0.85 suggested by Fanger for 80% acceptability is 18.1°C to 26.3°C, which is 1 to 2 degrees narrower on either side than the TSV comfort bands. Fanger's model is therefore underestimating the adaptive potential of the Azraq and Zaatari population. This is expected as the PMV model has been shown to predict narrower comfort ranges by several researchers [13]. This also indicates that the PMV is not a suitable model for use under such circumstances. The slope of the PMV regression line is 0.21/°C which is much lower than Fanger's 0.33/°C [7]. By contrast, our slope for the summer season (in which people had limited means of adaptation) is 0.31/°C (i.e. close to that given by PMV) supporting the observation that the PMV is only a suitable indicator of thermal comfort when people have limited or no adaptation opportunities (Table 8).

Table 8. Linear regression for PMV.

		α(/°C)	*b*	p-value	R^2	$T_n \pm SE$(°C)
PMV	Overall	0.2074	-4.6050	0.000	0.955	22.2±0.50
	Summer	0.3146	-8.0401	0.000	0.988	25.6±0.15
	Winter	0.1783	-4.0062	0.000	0.830	22.5±0.70

5.3.6 Logistic regression

As explained in the methodology, we used both linear and logistic regression to analyse our data. This double approach allows us to compare our outcomes to other research papers as well as validate them by using two different techniques.

Logistic regression was conducted for the TSV following the approach used by [19, 55, 61]. This allows us to compare the comfort temperature band derived from the logistic regression model with the one predicted by the linear model. The objective variable to be modelled is therefore the thermal sensation vote, which takes ordinal values in the range of [-3, 3]. For the application and analysis of the logistic model, it is more suitable to reduce the seven categories to the three classes *cold*, *comfortable*, *hot*, with:

- $TSV < -1$ classified as *cold*,
- $-1 \leq TSV \leq 1$ classified as *comfortable*,
- $TSV > 1$ considered as *hot*.

The internal operative temperature (T_o) is the predictor since we are interested in identifying the comfort temperature bands of the occupants. It is worth noting that, while the linear methods used binned data, the logistic model is fitted by using the separate votes of the individuals, hence the dis(comfort) probabilities of Figure 13 are only shown for reference.

After the regression was computed, the probabilities (given by equation (6)) of having a hot, $P(TSV > 1)$, cold, $P(TSV < -1)$, and comfortable, $P(-1 \leq TSV \leq 1)$ vote; are then given by the following equations derived by fitting the logistic regression to the data:

$$P(TSV > 1) = \frac{exp\{-11.1786+0.3437To\}}{1+exp\{-11.1786+0.3437To\}} \tag{9}$$

$$P(TSV < -1) = \frac{exp\{4.2310-0.3252To\}}{1+exp\{4.2310-0.3252To\}} \quad \text{and} \tag{10}$$

$$P(-1 \leq TSV \leq 1) = 1 - \{P(TSV > 1) + P(TSV < -1)\} \tag{11}$$

All the coefficients are statistically significant at p<0.001.

According to the ASHRAE thermal comfort standard 55-2013 [23], a thermal environment is regarded as comfortable when more than 80% of the occupants find it thermally acceptable; in terms of thermal sensation vote (TSV), this means that they are feeling between ‘slightly cool’ and ‘slightly warm’. In other words, the comfort band range is the range of temperatures which correspond to a probability of having $P(-1 \leq TSV \leq 1)$ higher than 80% as predicted by the logistic model. Based on this criterion, the comfort temperature band for the occupants of Azraq and Zaatari camps spans from 17.2°C to 28.4°C (Figure 13). This comfort band is only slightly tighter than the one predicted using the linear method (16.8°C to 28.5°C).

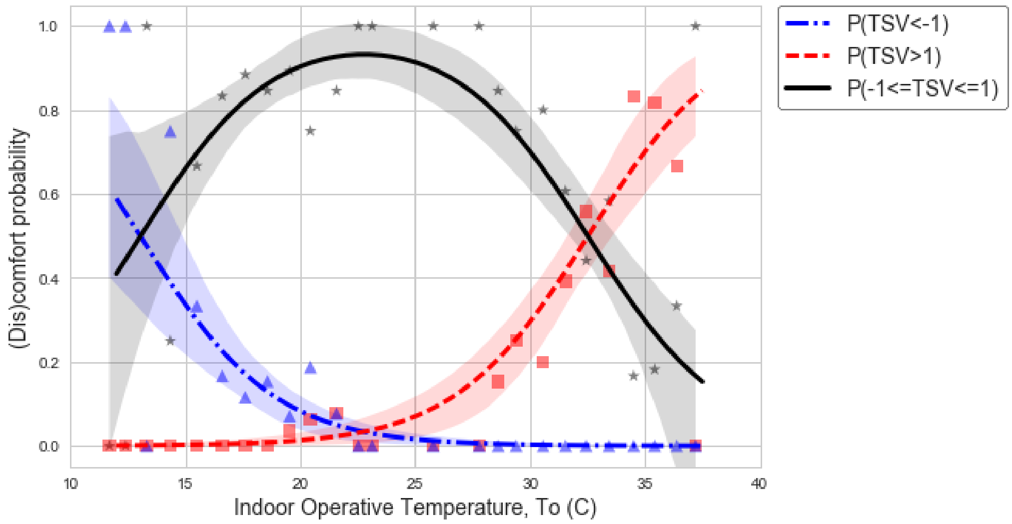


Figure 13: Dis(comfort) probability for the multinomial logistic model with 95% confidence bands. TSV-based T_n = 22.8°C.

5.3.7 Multiple logistic regression

Simple logistic or linear regression assumes that a single variable (in our case T_o) explains the response of the population. However, it is likely that other variables play a part, and knowing their relative influence would be of use in informing the design of more appropriate shelters. A multiple regression framework can be used to calculate the influence of each variable.

The selected potential predictor variables were:

- T_a (internal air temperature, °C),
- RH (internal relative humidity, %),
- T_g (internal globe temperature, °C)
- I_{cl} (clothing insulation, clo),
- V_a (internal air speed, m/s),
- MET (metabolic rate of the subject, met),
- SEX (0=male/1=female),
- AGE (age of the subject, years),
- CAMP (0=Azraq/1=Zaatari).

T_o was not used because it includes some of the other variables (T_a and V_a) in its definition. Prior to the analysis, the continuous variables were standardized by subtracting the mean and dividing by the standard deviation; this makes it possible to directly compare the dimensionless coefficients generated (Table 9 and 10).

Table 9. Results of the multiple logistic regression (summer).

	coef	SE	p-value	[95.0% conf. int.]	
Intercept	-2.4804	0.32	0.000	-3.10	-1.86
Ta	2.9522	0.41	0.000	2.14	3.76
Va	-0.7506	0.23	0.001	-1.20	-0.30
I_{cl}	0.7335	0.31	0.018	0.13	1.34

Table 10. Results of the multiple logistic regression (winter).

	coef	SE	p-value	[95.0% conf. int.]	
Intercept	-4.0257	0.58	0.000	-5.17	-2.89
Ta	-2.5446	0.57	0.000	-3.66	-1.43
Va	0.5951	0.21	0.004	0.19	1.00

As would be expected, T_a was found to be the most important predictor of discomfort in both summer and winter (Table 9 and 10). CAMP, AGE, SEX and RH were found not to be significant predictors, this means that occupant thermal perception does not statistically differ between the camps and that AGE, RH and SEX does not influence TSV. It is interesting that relative humidity in both camps and during both seasons is extremely low, this would facilitate thermal adaptation, as the cooling due to sweating is enhanced [62]. I_{cl} was found to be a significant predictor for hot discomfort (i.e. in summer) but not for cold discomfort (i.e. winter), while V_a is a statistically significant predictor for both. At increasing air speeds the discomfort temperature increases for both women and men in winter, for example, if air temperature remained constant, a 0.1 m/s increase in air speed, means a 13% *increase* in the probability of having a cold vote. While by holding I_{cl} and T_a fixed, a 0.1m/s increase in V_a, means a 17% *decrease* in the probability of having a hot vote (Figure 14). High I_{cl} values in summer increase the thermal sensation vote of occupants (Figure 14). This suggests that future shelter design should allow occupants to have the privacy needed for adapting their clothing to minimum desirable levels, for example by the covering of windows, and yet not restrict air movement—a potential design tension.

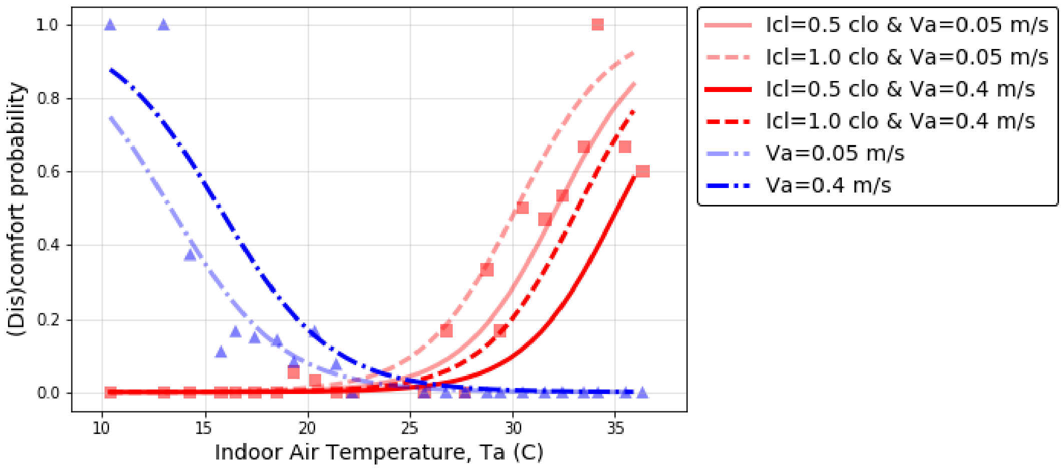


Figure 14: Dis(comfort) probability for 1°C operative temperature intervals and fitted multiple logistic models for the probability of having a hot (red) and cold (blue) vote at different I_{cl} and V_a values.

That I_{cl} is a predictor of comfort is not surprising as it is widely accepted that clothing levels have a significant influence on peoples' thermal sensation [23, 39, 42]. A change of 1clo corresponds to approximately 6°C in the neutral temperature [23]. (The adaptive thermal comfort theory assumes that occupants are able to adapt to their environment by changing their clothing [23].)

We found that an increase of 0.5 in I_{cl} corresponded to a 53% increase in the probability of having a hot vote, assuming the air temperature and air speed remained constant. The limited ability, especially of female respondents, to adapt clothing in summer undoubtedly contributed to their higher sensitivity shown in 5.3.4. In winter, respondents were dressed for the outdoors even while being indoors, wearing multiple layers and sometimes even outdoor coats or jackets, this explains the high I_{cl} values shown in Figure 15. In winter, the need to dress for the outdoors while being indoors in order to keep warm, not only illustrates aspects of the current shelter designs but has also probably contributed to some of the neutral votes given, despite the low temperatures recorded. A study in central southern China in winter [63] obtained a neutral temperature of 11.5°C for rural populations and 14°C for urban populations. The study attributed such low neutral temperatures to the high mean I_{cl} (2 clo) of the surveyed population, in addition to psychological adaptation. A study in Iran [22] showed a low correlation between T_o and clothing insulation in summer but a greater correlation in winter due to similar cultural issues as those faced in this study; in which people were dressed to the minimum socially acceptable limit in summer, while in winter they were freer to choose the level of clothing that would make them comfortable.

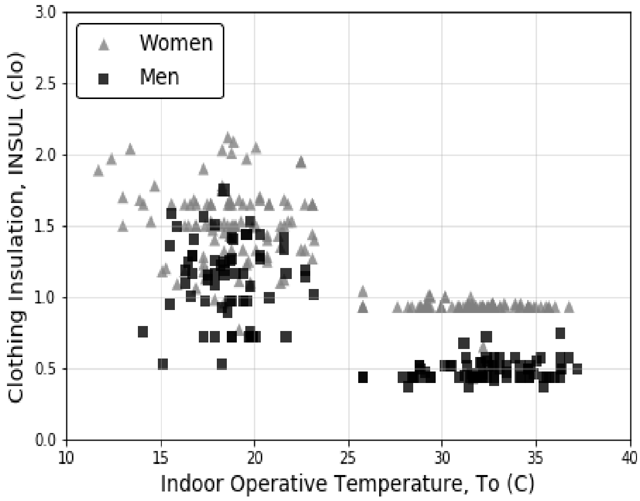


Figure 15: Female clothing insulation diversity was very restricted in summer, with almost no variations in I_{cl}. In addition, I_{cl} of women in summer is twice that of men.

5.4. Comparison with the Adaptive Standards

It is interesting that the T_n calculated using linear regression for TSV (22.7°C), for TPV (23°C), and using multinomial logistic regression for TSV (22.8°C) are so close, approximately 23°C. However, one of the main implications of the adaptive theory is that thermal neutrality is not the same between seasons, and that it is expected to be higher in summer and lower in winter, this is exactly what we see when we seasonally separate the data. Indeed, the T_n we calculated for each season fits well with the ASHRAE-55 comfort bands using the historical outdoor monthly mean temperature of the two locations (Azraq and Mafraq obtained from [27]) (Figure 16).

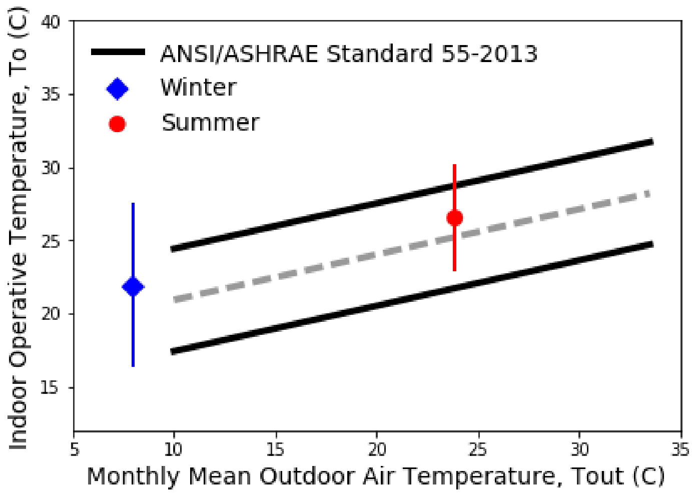


Figure 16: Neutral temperature and comfort limits found in this study in relation to the ASHRAE adaptive model.

6. Conclusions

This work represents the first such work with this understudied population of refugees living in camps; in addition, we publish a new questionnaire for use in foreign languages (see appendix B). We believe that our approach to conducting a survey, where the correct meaning of the ASHRAE scale terminology was achieved through a numerical approach rather than using a description, could be used in other languages were literal translation from English could not be used. In addition, given the use of interviews, rather than questionnaires completed by the respondents unaided, added rigour by giving the potential to explain the meaning of the questions and stressing that the questions related to the present moment, rather than feelings of comfort in general over past week or month. Plotting the TPV and TSV cumulative probability distributions against each other, showed that our new survey method gives the same neutral point for both approaches, and neutral temperatures within 0.3°C of each other. Thereby strongly validating our approach and solving the issues previous researchers reported with respect to translating the comfort scales into other languages.

The main findings are:

- Provision of security and safety were cited as the most important considerations in the design of a shelter, then thermal comfort, then privacy. 75% of the families were satisfied or very satisfied with the safety of their shelters.
- Fanger’s predicted mean vote model was found to underestimate the adaptive potential of the population, with the refugees more adapted to higher temperatures than predicted

by the PMV. This suggests that the PMV is not a suitable model for use under such circumstances.

- The majority of families reported that they found their shelters to be unbearably hot in July and August, while they also found it freezing in winter especially at night.
- Overall, a higher thermal satisfaction level was reported in winter than in summer.
- 50% of the families in Azraq reported having limited ability to adapt their clothes, especially women; while only 35% felt the same in Zaatari. This is mainly because Zaatari residents had more freedom in adapting their shelters to create a more private space while still allowing ventilation.
- The coolth of the concrete flooring was desired in summer, but was frequently reported as a source of discomfort in winter. Other sources of discomfort cited were gaps and draughts around the structure (68%), and the building materials used in the shelters (55%).
- Most refugees wore many layers of clothing when indoors in winter and used evaporative cooling to achieve comfort in summer—including showering with clothes on.
- All three assessments and analysis methods gave the same neutral temperature (T_n), 23°C.
- When T_n was calculated separately for each season using linear regression for TSV, the summer T_n was 4.7K higher than winter, fitting well with the ASHRAE adaptive model.
- The summertime T_n was found to be 4.2K lower when calculated using the TPV linear regression equation than with TSV. While in winter it was 3.5K higher when using TPV. Such discrepancy between the T_n(TSV) and T_n(TPV) for each season is much higher than that observed in literature and therefore could not be explained by the "semantic artefact hypothesis" alone.
- The comfort band found using logistic regression ranged from 17.2°C to 28.4°C – suggesting a significant adaptability of the refugees, but not one equal to the temperature range found on site.
- The level of clothing and the air speed were found to highly influence the TSV.
- Tensions between the need for ventilation, privacy, security and avoiding sand ingress were identified, and this points to a need to re-evaluate shelter ventilation in general. However, given the extreme conditions recorded, natural cross ventilation alone will not be sufficient in achieving summer comfort. Combining this with the observation that, due to safety and lack of resource, the refugees have no means of heating at night, a shelter solution that successfully includes better insulation, and possibly thermal mass would seem important.

Acknowledgment

This research was funded by EPSRC (EP/P510907/1) and was conducted in collaboration with UNHCR Jordan and NRC Jordan. We thank Prof Abdullah Alzoubi and Dr Omar Bani-Ahmad Otum from PSUT for their efforts in facilitating our data collection in the camps, and Ahmad Otum and Ahmad Muhaisen (PSUT) and Zain Aboabeid (Bath) for help with conducting the surveys. We also thank Scarlett-Tiger Coley for her photography, and Dr John Orr and Dr Stephen Lo (Bath) for their comments on the social survey.

References

[1] UNHCR, Figures at a glance http://www.unhcr.org/uk/figures-at-a-glance.html , 2017 (accessed 14 April 2017)

[2] UNHCR, Statistical yearbook 2014, 14th edition, statistical annexes, 2015. http://www.unhcr.org/statisticalyearbook/2014-annex-tables.zip

[3] IDMC, International Displacement Monitoring Centre database http://www.internal-displacement.org/database/, 2017 (accessed 14 April 2017)

[4] IDMC, Global overview 2015: People internally displaced by conflict and violence. International Displacement Monitoring Centre, Geneva, 2015 available at http://www.internal-displacement.org/assets/library/Media/201505-Global-Overview-2015/20150506-global-overview-2015-en.pdf (accessed 14 April 2017)

[5] UNHCR executive committee of the high commissioner's programme. Protracted refugee situations (2004), http://www.unhcr.org/40c982172.pdf (accessed 14 April 2017)

[6] M. Lee, L. Shi, A. Zanobetti, J.D. Schwartz, Study on the association between ambient temperature and mortality using spatially resolved exposure data, Environmental research. 151 (2016) 610-617 https://doi.org/10.1016/j.envres.2016.08.029

[7] P.O. Fanger, Thermal Comfort. 1970, Copenhagen: Danish Technical Press.

[8] J.F. Nicol & M.A. Humphreys, Thermal comfort as part of a self-regulating system, Building Research and Practice (J. CIB) 6(1973),191-197

[9] L. Heschong, Thermal delight in Architecture, MIT press, Cambridge, 1979

[10] R.J. de Dear, G.S. Brager. Developing an adaptive model of thermal comfort and preference. ASHRAE Transactions, 1998.

[11] J.F. Nicol and M.A. Humphreys, Adaptive thermal comfort and sustainable thermal standards for buildings. Energy and Buildings, 34 (2002), 563-572. https://doi.org/10.1016/S0378-7788(02)00006-3

[12] R.J. de Dear, T. Akimoto, E.A. Arens, G. Brager,C. Candido, K.W. Cheong, B. Li, N. Nishihara, S.C. Sekhar, S. Tanabe, J. Toftum, H. Zhang, Y. Zhu, Progress in thermal comfort research over the last twenty years. Indoor Air, 23, (2013) 442-61

[13] M. Indraganti, R. Ooka, H.B. Rijal, Thermal comfort in offices in summer: Findings from a field study under the 'setsuden' conditions in Tokyo, Japan. Building and Environment, 2013. 61: p. 114-132.

[14] S. A. Zaki, S.A. Damiati, H.B. Rijal, A. Hagishima, A. Razak, Adaptive thermal comfort in university classrooms in Malysia and Japan. Building and Environment, 122 (2017), p. 294-306

[15] H.B. Rijal, H. Yoshida, N. Umemiya, Seasonal and regional differences in neutral temperatures in Nepalese traditional vernacular houses, Building and Environment 45 (2010) 2743-2753 https://doi.org/10.1016/j.buildenv.2010.06.002

[16] J. C. Brown, and P. J. Jones, Thermal Comfort in Modern Industrial Buildings, Clima 2000 Conference, London, Chartered Institute of Building Services Engineers (1993).

[17] R.J. deDear, and M.E. Fountain, Field experiments on occupant comfort and office thermal environments in a hot- humid climate, ASHRAE Transactions, 100, 2, (1994), 457-475.

[18] G. E. Schiller, A comparison of measured and predicted comfort in office buildings. ASHRAE Transactions, 96,1, (1990),

[19] M. Indraganti, Thermal comfort in naturally ventilated apartments in summer: Findings from a field study in Hyderabad, India. Applied Energy, 87, 3, (2010), 866-883.

[20] M.A. Ealiwa, A.H. Taki, A.T. Howarth, M.R. Seden, An investigation into thermal comfort in the summer season of Ghadames, Libya. Energy and Buildings, 36 (2001), 231-237

[21] C. Bouden, N. Ghrab, An adaptive thermal comfort model for the Tunisian context: a field study results. Energy and Buildings, 37 (2005), 952–963. https://doi.org/10.1016/j.enbuild.2004.12.003

[22] S. Heidari, S. Sharples, A comparative analysis of short-term and long-term thermal comfort surveys in Iran, Energy and Buildings, 34, 6, (2002) 607-614. https://doi.org/10.1016/S0378-7788(02)00011-7

[23] ASHRAE, Thermal Environmental Conditions for Human Occupancy, ASHRAE Standard 55, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta, Georgia, 2013, 2004, 2010.

[24] M. Luo, R. deDear, W. Ji, C. Bin, B. Lin, Q. Quyang, Y. Zhu, The dynamics of thermal comfort expectations: The problem, challenge and impication, Building and Environment. 95 (2016), 322-329.

[25] M. Kottek, J. Grieser, C. Beck, B. Rudolf, F. Rubel, World map of the Köppen-Geiger climate classification updated, Meteorol Z. 15 (2006), 259–263

[26] UNHCR data portal, Syria Regional Refugee Response: Inter-agency Information Sharing Portal. http://data.unhcr.org/syrianrefugees/regional.php (accessed on 14 April 2017)

[27] Food and Agriculture Organization of the United Nations FAO 2017, CLIMWAT 2.0 software, available online from http://www.fao.org/land-water/databases-and-software/climwat-for-cropwat/en/ (accessed on 14 April 2017)

[28] IFRC, UN-HABITAT and UNHCR, Shelter projects 2013-2014. ShelterCaseStudies 2014 Available online from www.sheltercasestudies.org

[29] Reach, Azraq camp shelter assessment: assessment report January 2015. UNHCR, Jordan, 2015.

[30] M.A. Humphreys, H.B. Rijal, and J.F. Nicol, Updating the adaptive relation between climate and comfort indoors; new insights and an extended database. Building and Environment, 63 (2013), 40-55.

[31] M. Luo, B. Cao, J. Damiens, B. Lin, Y. Zhu, Evaluating thermal comfort in mixed-mode buildings: A field study in a subtropical climate. Building and Environment 88 (2015), 46-54

[32] M.R. Sharma, and S. Ali, Tropical Summer Index – A Study of Thermal Comfort of Indian Subjects, Building and Environment, Pergamo, 21 (1986), 11-24.

[33] M.S. Mustapa, S.A. Zaki, H.B. Rijal, A. Hagishima, M.S.M. Alia, Thermal comfort and occupant adaptive behaviour in Japanese university buildings with free running and cooling mode offices during summer. Building and Environment, 105 (2016), 332-342.

[34] M. Indraganti, K.D. Rao, Effect of age, gender, economic group and tenure on thermal comfort: A field study in residential buildings in hot and dry climate with seasonal variations. Energy and Buildings, 42 (2010), 273-281

[35] A.C. Ogbonna and D.J. Harris, Thermal comfort in sub-Saharan Africa: Field study report in Jos-Nigeria. Applied Energy, 85 (2008), 1-11

[36] H. Feriedi and N.H. wong, Thermal comfort for naturally ventilated houses in Indonesia. Energy and Buildings, 36, (2004), 614-624

[37] M. Takasu, R. Ooka, H.B. Rijal, M. Indraganti, M.K. Singh, Study on adaptive thermal comfort in Japanese offices under various operation modes, Building and Environment, 'in press' 10.1016/j.buildenv.2017.02.023

[38] BS EN ISO 7726: 2001, Ergonomics of the thermal environment - Instruments for measuring physical quantities, European Committee for Standardization, 2001.

[39] F. Nicol, M.A. Humphreys, S. Roaf, Adaptive thermal comfort: principles and practice, London: Routledge, 2012

[40] BS EN ISO 9920: 2009, Ergonomics of the thermal environment - Estimation of thermal insulation and water vapour resistance of a clothing ensemble (ISO 9920:2007, Corrected version 2008-11-01), European Committee for Standardization, 2009

[41] G. Havenith, K. Kuklane, J. Fan, S. Hodder, Y. Ouzzahra, K. Lundgren, Y. Au, D. Loveday, A database of static clothing thermal insulation and vapour permeability values of non-western ensembles for use in ASHRAE Standard 55, ISO 7730, and ISO 9920 CH-15-018 (RP-1504). ASHRAE Transactions, 121,1, (2015), 19pp.

[42] F.F. Al-ajami, d.L. Loveday, K.H. Bedwell, G. Havenith, Thermal insulation and clothing area factors of typical Arabian Gulf clothing ensembles for males and females: Measurements using thermal manikins, Applied Ergonomics, 39 (2008), 407–414.

[43] ISO 7730: 2005, Ergonomics of the Thermal Environment d Analytical Determination and Interpretation of Thermal Comfort Using Calculation of the PMV and PPD Indices and Local Thermal Comfort Criteria, European Committee for Standardization, UK, 2006.

[44] S. Natarajan, J. Rodrigos, M. Vellie, A field study of indoor thermal comfort in the subtropical highland climate of Bogota, Colombia, J. Build. Eng., 4 (2015), 237–246

[45] M.A. Humphreys, F. Nicol, S. Roaf, Adaptive thermal comfort: Foundation and analysis (Vol 2), Abingdon: Routledge, 2016

[46] A.K. Mishra, and M. Ramgopal, An adaptive thermal comfort model for the tropical climatic regions of India (Köppen climate type A). Building and Environment, 85 (2015), 134-143.b

[47] W. Yang, and G. Zhang, Thermal comfort in naturally ventilated and air-conditioned buildings in humid subtropical climate zone in China. International Journal of Biometeorology, 52(2008), 385-398.

[48] A. Farghal, and A. Wagner. Studying the adaptive comfort model a case study in a hot dry climate, Cairo, Egypt. . in Adapting to Change: New Thinking on Comfort. 2010. Windsor, UK.

[49] L.G. Gomez-Azpeitia, G. Bojorquez, R.P. Ruiz-Torres, A. Tejeda, Extreme Adaptation to Extreme Environments in Hot Dry, Hot Sub-humid and Hot Humid Climates in Mexico. Journal of Civil Engineering and Architecture, 2014. 8(8): p. 929-942.

[50] S. Dhaka, J. Mathura, G. Bragerb, A. Honnekerib, Assessment of thermal environmental conditions and quantification of thermal adaptation in naturally ventilated buildings in composite climate of India. Building and Environment, 2015. 86(0): p. 17-28.

[51] S. Dhaka, J. Mathura, A. Wagner, Evaluation of thermal environmental conditions and thermal perception at naturally ventilated hostels of undergraduate students in composite climate. Building and Environment, 2013. 66(0): p. 42-53.

[52] T.H. Karyono, Report on thermal comfort and building energy studies in Jakarta—Indonesia. Building and Environment, 2000. 35(1): p. 77-90.

[53] A.T. Nguyen, M.K. Singh, and S. Reiter, An adaptive thermal comfort model for hot humid South-East Asia. Building and Environment, 2012. 56: p. 291-300.

[54] H. Djamila, C.C. Ming, S. Kumaresan, Investigation on Indoor Thermal Satisfaction in the Humid Tropics of Malaysia. Journal of Multidisciplinary Engineering Science and Technology (JMEST), 2 (2015)

[55] F. Haldi, and D. Robinson, On the unification of thermal perception and adaptive actions. Building and Environment, 2010. 45(11): p. 2440-2457.

[56] J. Engel, Polytomous logistic regression. Statistica Neerlandica, 1988. 42(4): p. 233-252.

[57] S.S. Shapiro, and M.B. Wilk, An analysis of variance test for normality (complete samples). Biometrika, 1965. 52(3-4): p. 591-611.

[58] M. Indraganti, R. Ooka, H.B. Rijal, G.S. Brager, Adaptive model of thermal comfort for offices in hot and humid climates of India. Building and Environment, 74 (2014), 39-53 https://doi.org/10.1016/j.buildenv.2014.01.002

[59] S.A. Damiati, S.A. Zaki, H.B. Rijal, S. Wonorahardjo. Field study on adaptive thermal comfort in office buildings in Malaysia, Indonesia, Singapore, and Japan during hot and humid season. Building and Environment, 109 (2016), 208-223 https://doi.org/10.1016/j.buildenv.2016.09.024

[60] S. Karjalainen, Thermal comfort and gender: a literature review. Indoor Air. 22(2012):96-109. doi: 10.1111/j.1600-0668.2011.00747.x

[61] K.W. Mui, L.T. Wong, Neutral temperature in subtropical climates—A field survey in air-conditioned offices, Building and Environment, 42, 2, (2007), 699-706, ISSN 0360-1323, http://dx.doi.org/10.1016/j.buildenv.2005.10.021.

[62] Parsons, K., Human Thermal Environments: The Effects of Hot, Moderate, and Cold Environments on Human Health, Comfort and Performance, Second Edition. 2002: Taylor & Francis.

[63] J. Han, W. Yang, J. Zhou, G. Zhang, Q. Zhang, D.J. Moschandreas, A comparative analysis of urban and rural residential thermal comfort under natural ventilation environment. Energy and Buildings 41 (2009) 139–145.

Appendix A: Tables

Table A1: Instruments specification

Measurement	Type	Accuracy	Resolution	Range
Interior T_a , Interior T_g , Interior RH	Extech HT30 Heat Stress WBGT (Wet Bulb Globe Temperature) Meter	±1°C, ±2°C, ±3%	0.1°C 0.1°C 0.1%	0 to 50°C, 0 to 80°C, 0 to 100%
Interior V_a	ATP Hot wire anemometer	±5% of reading +0.1m/s	0.01m/s	0.1 to 25m/s
Weather station	Radio-Tech temperature and humidity sheilded sensor WindSonic ultrasonic anemometer Kipp & Zonen SP Lite Silicon Pyranometer	T_a < ±0.3K RH < 3% Wind Speed <±2% Direction <±3° <10%	0.01°C 0.01% 0.01m/s 1°	-10°C to +55°C 0 to 100% 0 to 60m/s 0 to 359° 0 to 2000 w/m^2 (T = -30°C to +70°C)

Table A2: ASHRAE standard sensation and preference scales and suggested Arabic translation

Numerical scale	ASHRAE sensation scale	ASHRAE Preference scale	Arabic sensation scale (Levantine dialect)	Arabic preference scale (Levantine dialect)
3	hot		حار جدا (كتير مشوب)	
2	warm	much warmer	حار (مشوب)	ادفى بكثير (كتير ادفى)
1	slightly warm	A bit warmer	حار قليلا جدا (شوي مشوب)	ادفى بقليل (شوي ادفى)
0	neutral	no change	حيادي (حيادي)	لا تغير (لا تغير)
-1	slightly cool	A bit cooler	بارد قليلا جدا (بارد شوي)	ابرد بقليل (شوي ابرد)
-2	cool	much cooler	بارد (برد)	ابرد بكثير (كتير ابرد)
-3	cold		بارد جدا (بارد كتير)	

Appendix B: The adapted thermal comfort questionnaire published in English to allow translation to other languages (Levantine dialect):

Part 1: Thermal Sensation

Thermally speaking, at this moment in time, are you feeling absolutely neutral or feeling a sensation of heat or coolth (no matter how little)

a	neutral	**(حيادي)**
b	a sensation of heat	(شعور بالشوب)
c	a sensation of coolth	(شعور بالبروده)

if b, from scale of 1 to 3 how hot are you feeling, with one being a little bit (شوي)**and 3 being a lot** (كتير)

1 2 3

if c, from scale of 1 to 3 how cold are you feeling, with one being a little bit (شوي)**and 3 being a lot** (كتير)

1 2 3

Part 1 Summary:

Answer	Numerical scale	Corresponding ASHRAE scale
b3	3	Hot
b2	2	Warm
b1	1	Slightly warm
a	0	Neutral
c1	-1	Slightly cool
c2	-2	Cool
c3	-3	Cold

Part 2: Thermal Preferences

1) **At this moment in time, do you prefer a change or no change in your thermal environment**

a	no change	**(لا تغير)**
b	change/toward warmth	(تغير للادفء)
c	change/toward cold	(تغير للابرد)

2) **if b, from scale of 1 to 2 how much warmer would you like it to be compared to NOW**

1	a little bit	**(شوي)**
2	a lot	(اكتر)

3) if c, from scale 1 to 2 how much colder would you like it to be compared to NOW

1	a little bit	**(شوي)**
2	a lot	(اكتر)

<u>Part 2 Summary:</u>

Answer	Numerical scale	Corresponding Preference scale
b2	2	Much warmer
b1	1	A bit warmer
a	0	No change
c1	-1	A bit cooler
c2	-2	Much cooler

Appendix

Probabilistic adaptive thermal comfort

This research forms part of the project COLBE (The Creation of Localized and Future Weather for the Build Environment) funded by the EPSRC. The project aims to define a method to create local weather files from 2015 to 2080 covering the whole UK at a resolution of 5 km, and to include files that represent various excursions from the mean: e.g. heat waves and cold snaps. The work reported in this paper represent a preliminary study on the creation of a probabilistic adaptive model that takes into account weather variability when designing naturally ventilated buildings around the world.

As part of this work, a new probabilistic adaptive comfort theory is introduced which provides new comfort equations for resilient building design. The year-on-year weather variability is shown to greatly depend on the location. This implies that in some locations the potential error created by using a single representative year will be greater than in others. Our new probabilistic method is able to take into account this weather variability and promote a resilient building design in any location around the world.

This work is totally based on a same-titled paper published in Building and Environment in 2015, more details are provided below.

Declaration of Authorship

This declaration concerns the article entitled: Probabilistic adaptive thermal comfort for resilient design	
Status	Published in Building and Environment.
Details	David Coley, Manuel Herrera, Daniel Fosas, Chunde Liu & **Marika Vellei**, Probabilistic adaptive thermal comfort for resilient design, Building and Environment, 2015, Volume 123, Pages 109-118. DOI: doi.org/10.1016/j.buildenv.2017.06.050
Authors' contribution	The author of this thesis contributed to the statistical analysis (30%) and to writing the manuscript (40%) but the main idea and methodology came from the first two authors of the paper (D. Coley and M. Herrera). Each author's exact contribution to the article is outlined below: D. Coley: Formulation of ideas (80%), Design of methodology (80%), Preparation of the manuscript (60%). D. Fosas: Simulation Work (100%). M. Herrera: Formulation of ideas (10%), Design of methodology (10%), Processing/Analysis of data (70%). **M. Vellei**: Formulation of ideas (10%), Design of methodology (10%), Processing/Analysis of data (30%), Preparation of the manuscript (40%).
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.
Date and Signature	

Probabilistic adaptive thermal comfort for resilient design

David Coley[a], Manuel Herrera[a], Daniel Fosas[a], Chunde Liu[a] and Marika Vellei[a,*]
[a]*EDEn - Department of Architecture & Civil Engineering*
University of Bath, Claverton Down, Bath, BA2 7AY, United Kingdom

[*]Corresponding author: *m.vellei@bath.ac.uk*

Abstract

Adaptive thermal comfort theory has become the bedrock of much thinking about how to judge if a free-running environment is suitable for human occupation. In design work, the conditions predicted by a thermal model, when the model is presented with one possible annual weather time series (a reference year), are compared to the limits of human comfort. If the temperatures are within the comfort limits, the building is judged to be suitable. However, the weather in many locations can vary year-on-year by a considerable margin, and this begs the question, how robust are the predictions of adaptive comfort theory likely to be over the many years a building might be in use? We answer this question using weather data recorded for up to 30 years for locations within each of the five major Köppen climate classifications. We find that the variation in the annual time series is so great that the predicted comfort temperature frequently lies outside the acceptable range given by the reference year. Return periods for the excursions of the time series are calculated for each location. The results for one location are then validated using the world's longest temperature record. These results suggest that industry and academia would be best advised to move to a probabilistic methodology, like the proposed one, when using adaptive comfort theory to judge the likely conditions within a building. Extra pertinence is provided by concerns over increases in mortality and morbidity in buildings due to a rapidly warming climate.
Keywords: adaptive thermal comfort, robust building design, Test Reference Year, Design Summer Year

Highlights

- The variability of historical weather time series studied for locations within each of the five major Köppen climate classifications.
- A new probabilistic adaptive comfort theory introduced.
- New comfort equations for resilient building design presented.

1. Introduction

There has been a growing realisation that the use of a single air temperature to represent the preferred temperature of a group of occupants is invalid in the case of free-running buildings where occupants have the ability to adjust their environment, for example by altering clothing levels and opening windows. In such cases the preferred temperature is better represented by the adaptive thermal comfort theory. This accounts for the adaptation of the individuals to the external temperature during the previous days. As this results in preferred temperatures rising during the summer, and falling in winter, the approach can also lead to lower conditioning energy use [1, 2], and hence is a common strategy in low-energy design. The approach has been given extra weight by its adoption in building codes and regulations via the ANSI-ASHRAE Standard 55 [3] and the European EN-15251 [4].

To apply the approach during the design phase, a thermal simulation of the building is completed and the predicted temperatures are compared to those given by the adaptive thermal comfort theory (which generates a range of acceptable temperatures). If the temperatures inside the building are within this range, it is assumed that the occupants will in general be satisfied and no conditioning will be needed. This simulation requires a weather file for the location in question and, as in most design work, a single representative year of weather (observed or artificially created) is used. This begs the question, how different might the answer be if a different year of weather was used? I.e. when applied within a design setting, rather than a research one, how robust is the adaptive thermal comfort method. As the adaptive thermal comfort approach is used for simulating buildings without air conditioning, an error here can lead to fatal consequences. In the 2003 European heatwave 14,000 people died in Paris alone - almost all in free-running buildings [5]. As the predictions of climate change are for a much warmer world [6], with longer, more intense and more frequent heatwaves [7-9], there is a growing risk of heat-related morbidity and mortality [10-12] and a need to ensure resilient buildings.

Adaptive thermal comfort makes use of a running mean outdoor air temperature taken over the previous days. Hence there has been a tacit assumption that the smoothing of the weather data that this implies leads to a representative year giving acceptable temperatures that are very close to those that would occur in any real year.

In this paper we examine whether this is really so. This is achieved by using approximately thirty years of weather data recorded at five locations, one in each of the major climatic regions of the world according to the Köppen classification [13], and three additional locations in the UK, plus 3,000 years of synthetic data generated for the three UK locations. From this data, the range of acceptable temperatures is calculated and a series of statistical methods is applied to study how the data spans in both temperature and temporal space. This ultimately results in a new probabilistic adaptive thermal comfort model which can be directly used for the resilient design, via thermal simulation, of free-running buildings. The return periods of this model are validated for London against the Central England Temperature Record, which spans 358 years, from 1659 to today; then the predictions are themselves validated by comparing the excursions predicted by the model and those given by the weather generator.

1.1. Representative weather

Building simulation is normally based on the use of representative weather time series. These representative weather files summarise weather conditions for a location. This includes hourly data on temperature, dew point, direct and diffuse solar radiation, wind speed and wind direction, etc. These files are used to estimate the average building energy use and carbon emissions [14, 15]. A typical representative weather file is created from historical data (usually around 20-30 years of data, depending on data availability), and compiled by comparing the cumulative and empirical distribution functions of different meteorological variables within the base dataset.

The Test Reference Year (TRY), for example, is composed of 12 separate months of data each one chosen to be the most average month among a set of base years [16]. The cumulative distribution functions on which the TRY is based are made up of the daily mean values of three parameters: dry bulb temperature, cloud cover (used as a proxy for solar irradiation), and wind speed. These daily means are computed using hourly values from all the months of the base years considered. Component months are chosen using the Finkelstein-Schafer (FS) statistic method, essentially, those months with the most average values of temperature, radiation and wind speed combined. In the case of the TRY, each of the 3 environmental parameters carries an equal weighting; this was deemed an appropriate method for naturally ventilated buildings [16].

By contrast, the Design Summer Year (DSY) [16] is primarily an attempt to estimate the impact of warmer than average summers. It was initially intended for the sizing of mechanical cooling systems and is now used for assessing the risk of overheating in naturally ventilated buildings. The DSY is the year that falls in the middle of the upper-quartile of the base years' dataset, ranked according to summertime (April to September) average dry bulb temperature; this is generally the third warmest summer for a base dataset of 20 years. The DSY does not take into account extreme temperatures in individual months or incident solar radiation, both of which are of great significance for assessing the overheating performance of buildings [17]. This means that periods of high temperature (such as heat waves) in relatively cool summers are not considered. This is a problem, as summers such as 2003 which resulted in so many deaths across Europe are not ranked highly in the base dataset when considering average summertime temperature. Various attempts have been made to address such concerns, largely by creating new reference years based on warmer periods or on predictions of climate change (see, for example: [18-23]).

Although the DSY might be appropriate for measuring overheating duration it is unlikely to be suitable for looking at severity of overheating due to its simple selection method [24]. Weighted cooling degree hours have been suggested as an alternative metric for the selection of a DSY that might solve this [18, 25]. Furthermore, as it is known that different weather parameters have a differing influence on the relative risk of overheating for different building types [23], three design reference years were selected in [26] based on the daily mean temperature, relative humidity and solar radiation respectively. In addition, different sampling methods [26, 27] and statistical adjustment methods [28] have been used to develop new DSYs but none of them have been found to overcome all the shortcomings in the simple DSY selection discussed in [29].

Here we take a different approach by retaining the reference year and adding resilience by making the upper and lower bounds of the comfort equation probabilistic.

1.2. Adaptive thermal comfort

The adaptive thermal comfort theory was first introduced by Nicol and Humphreys in the 1970s [1]. An adaptive model was then incorporated into the ANSI/ASHRAE Standard 55 in 2004 thanks to the research of Brager and De dear [2] who assembled the ASHRAE RP-884 database from more than 21,000 thermal comfort measurements primarily in office buildings in Thailand, Indonesia, Singapore, Pakistan, Greece, UK, USA, Canada and Australia. The adaptive model of the ANSI/ASHRAE Standard 55 [3] and its European counterpart (EN 15251) [4] are driven by the idea that in free-running spaces there exists a wide band of temperatures within which an occupant can find his/her own optimum given sufficient adaptive opportunities.

According to the adaptive theory [2, 30], thermal comfort is not merely the result of a body's thermal balance but is the outcome of a continuous process of adaptation involving physiological, psychological and behavioural adaptation. The physiological responses of the human body to environmental stimuli have been widely studied in the literature [31-33]. Psychological adaptation includes any psychological reaction to sensory information, such as habituation, relaxation of thermal expectations and gradual change of preferences. Behavioural adaptation refers to all the conscious or unconscious actions that, when the environmental stimuli are perceived as discomforting, a person can take in order to modify the building indoor environment, their personal situation or both of these, such as taking on/off clothing, consuming hot/cold food and hot/cold drinks, opening/closing windows and doors, and drawing curtains. This is in agreement with the fundamental precept of the adaptive model: 'if a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort' [2]. Of the three forms of adaptive opportunities, this is the one in which occupants have the opportunity to play an active role.

Both the ASHRAE and European adaptive comfort models consider the process of thermal adaptation as a black box and integrate occupant thermal expectations and adaptive actions in a single linear equation predicting indoor comfort temperatures from outdoor temperatures. Within the ASHRAE adaptive thermal comfort model [3], the upper and lower allowable indoor operative temperature limits (T_{upper} and T_{lower}) depend on the outdoor temperature T_{out} (Figure 1):

$$T_{upper} = (0.31 \cdot T_{out} + 17.8) + 3.5, \text{ and} \tag{1}$$
$$T_{lower} = (0.31 \cdot T_{out} + 17.8) - 3.5 \tag{2}$$

where T_{out} is the prevailing mean outdoor air temperature which can be approximated by the exponentially-weighted running mean temperature. In this running mean α is set to 0.8 (the ANSI/ASHRAE Standard 55 suggests using a value between 0.6 and 0.9 [3]), hence the weights give more importance to the mean daily temperatures of recent days:

$$T_{out} = (1 - \alpha) \cdot [T_{e(d-1)} + \alpha \cdot T_{e(d-2)} + \alpha^2 \cdot T_{e(d-3)} + \alpha^3 \cdot T_{e(d-4)} + ...] \tag{3}$$

where $T_{e(d-1)}$ is the mean outdoor temperature of the day before the day in question, and $T_{e(d-2)}$ is the mean outdoor temperature of the day before that, and so on.

The centre point of these bounds, i.e. the comfort temperature (T_{comf}), is given by:

$$T_{comf} = 0.31 \cdot T_{out} + 17.8 \tag{4}$$

The ASHRAE adaptive limits are valid for spaces without any mechanical cooling system installed and with no heating system in operation, for prevailing mean outdoor air temperatures ranging between 10 and 33.5°C.

Greater detail of the background and use of the adaptive model can be found in references: [2, 30]. Despite a series of criticisms of this approach, especially regarding its accuracy when compared to Fanger's heat-balance model [34], this remains the most widely used model for designing free-running environments.

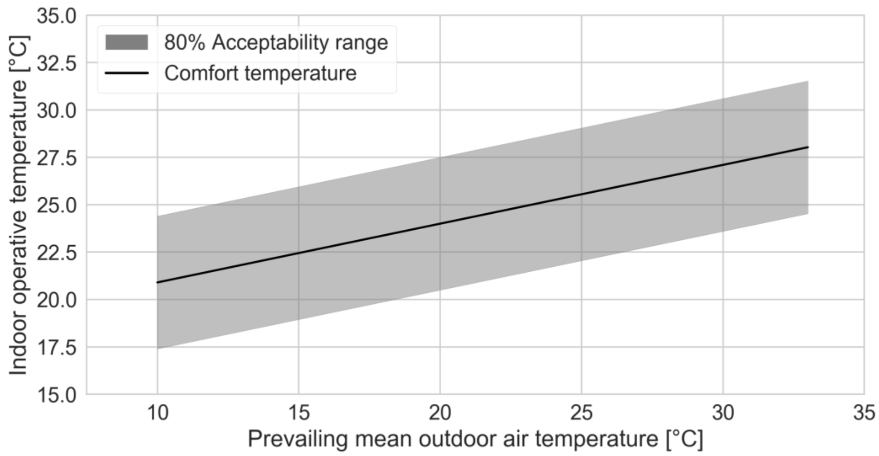


Figure 1: Acceptable operative temperature ranges for naturally conditioned spaces according to the ANSI/ASHRAE Standard 55-2013.

1.3. Köppen Climate Classifications

The Köppen Climate Classification System is the most widely used scheme for classifying climates [13]. Its categories are based on the annual and monthly averages of precipitation and temperature. It recognizes five major climatic types, each designated by a capital letter. Figure 2 shows the distribution of these climates.

Tropical Moist Climates (A)
Tropical moist climates extend north and south from the equator to approximately 15 to 25° of latitude. In these climates all months have average temperatures greater than 18°C and annual precipitation greater than 1.5 m.

Dry Climates (B)
In this climate potential evaporation and transpiration exceed precipitation. These climates extend from 20 to 35° north and south of the equator and in large continental regions of the mid-latitudes frequently surrounded by mountains.

Moist Subtropical Mid-Latitude Climates (C)
This climate commonly has warm and humid summers with mild winters. It extends from 30 to 50° of latitude mostly on the eastern and western borders of continents. During the winter, a dominant feature is a mid-latitude cyclone. Convective thunderstorms are common in summer.

Moist Continental Mid-Latitude Climates (D)
Moist continental mid-latitude climates with relatively warm to cool summers and cold winters, and existing pole-ward of the C climates. The average temperature of the coldest month is less than -3°C and the warmest month greater than 10°C. Winters would be considered severe with snowstorms, strong winds, and cold from continental polar or arctic air masses.

Polar Climates (E)
Polar climates are cold year-round and even the warmest month will be less than 10°C. Such climates are found on the northern coast of North America, Europe, Asia, and on the landmasses of Antarctica and Greenland.

The locations selected for the study are: Ceará (Brazil, Köppen A), Riyadh (Saudi Arabia, Köppen B), Sydney (Australia, Köppen C), Helsinki (Finland, Köppen D), and Nuuk (Greenland, Köppen E).

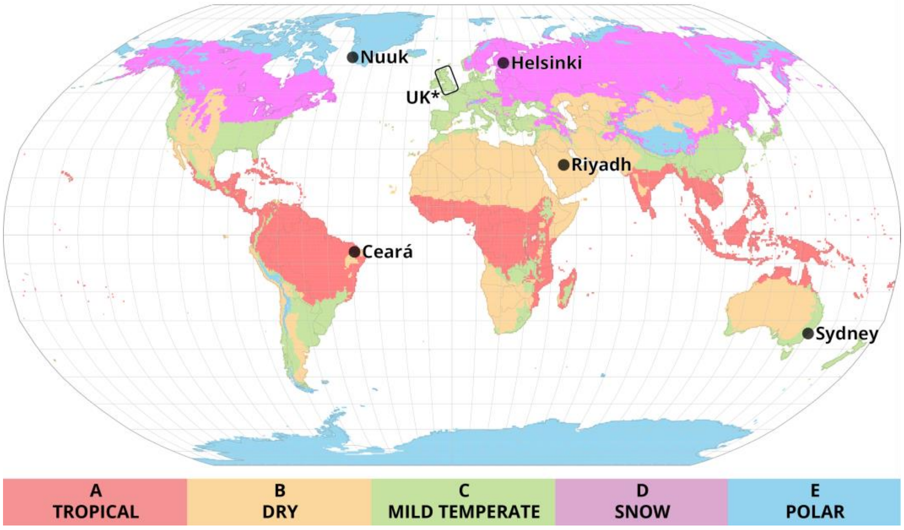


Figure 2: Major Köppen climate classifications; adapted from [13]. UK*: London, Manchester and Edinburgh.

2. Materials

In the following we introduce the historical and synthetic weather files used in this paper.

2.1. Base years

The National Centers for Environmental Information (NCEI), from the National Oceanic and Atmospheric Administration (NOAA), provides public access under request to a large database of global environmental data. This database was used to create the mean daily temperatures of the last thirty years (up to 2015) of five locations (Ceará, Riyadh, Sydney, Helsinki and Nuuk) corresponding to the five Köppen regions (A-E). In the case of Sydney, only 18 years of data were available.

In addition, the British Academic Data Centre (BADC) repository [35] was used to create 22 years of data for London, Manchester, and Edinburgh in the UK (Köppen C), and to build TRY and DSY.

2.2. Synthetic Weather

Given the limitations in the length of the historical weather record in many locations, interest has grown in the use of synthetic weather data produced by weather generators. These programs use the observed long-term statistical weather record at a location to produce an hourly time series of the common weather variables.

Two advantages of weather generators over other data sources are that they can provide a near infinite number of possible years of weather, and they can be run into the future, thereby accounting for climate change. The weather generator used in this work was that used by the UK Climate Impacts Programme [36]. The probabilistic projection methodology in UKCP09 involves sampling climate modelling uncertainties by combining results from perturbed variants of the UK Met Office global climate model (HadCM3) with projections from an ensemble of four alternative international climate models used by the fourth IPCC assessment report [37]. Running the weather generator involves declaring a time period and a world carbon emission scenario. In this work the time slice was set to the 2020s, as this is the closest to the current date, and the emission scenario to low (to create the minimum perturbation from current weather). 3,000 years of weather was generated for London, Edinburgh and Manchester.

2.3. Central England Temperature Record

The Central England Temperature record was originally published by Gordon Manley in 1953 and subsequently extended and updated in 1974 [38], following many decades of work. The mean surface air temperatures, for the Midlands region of England, are given from the year 1659 to the present (daily since 1772). This record represents the longest series of temperature observations in existence.

3. Methods

The methodology is presented in Figure 3 and consists of the following steps:

1. Extract the multi-year daily weather time series for all the study locations (one in each of the five major Köppen climate classifications and three in the UK) and create the representative years for the UK locations (London, Edinburgh and Manchester). Any missing data in the observed time series was replaced with data just prior to the missing section.
2. Use equations (1) to (4) to transform the multi-year and representative temperature time series to comfort indoor temperature time series for all locations around the world. The calculation of the running mean outdoor air temperature requires a warming up period, which varies depending on how many days are being considered for its calculation. For example, a 30-days running mean cannot be computed for the first 30 days of January using data for a single year. In such situations, the running mean is calculated using data from December of the same year as an approximation.
3. Compute the mean of the daily standard deviations of the temperature time series for each location and compare them in order to judge their variability; repeat for the running mean time series.
4. For London, Edinburgh and Manchester, compare the upper and lower bounds of the comfort temperature given by the reference years to the range given by the complete multi-year set of comfort temperatures in order to discover if days exist that are outside the bounds given by the representative comfort years.
5. Compute the mean of the daily standard deviations for the 3,000 years of synthetic weather generated for London, Edinburgh and Manchester. If this matches that given by the historical weather records, compute return periods for any excursions of the running mean time series. A return period is an estimate of the regularity with which a

certain event will occur. So, if a return period is N, it is expected to occur once every N years. In our case the event is the excursion in the running mean time series.

6. Create a new set of *probabilistic* adaptive comfort equations based on these return periods.
7. Validate the return periods by using 358 years of data from the Central England Temperature Record; then the predictions themselves by comparing the excursions predicted by the model and those given by the weather generator for a different time period.

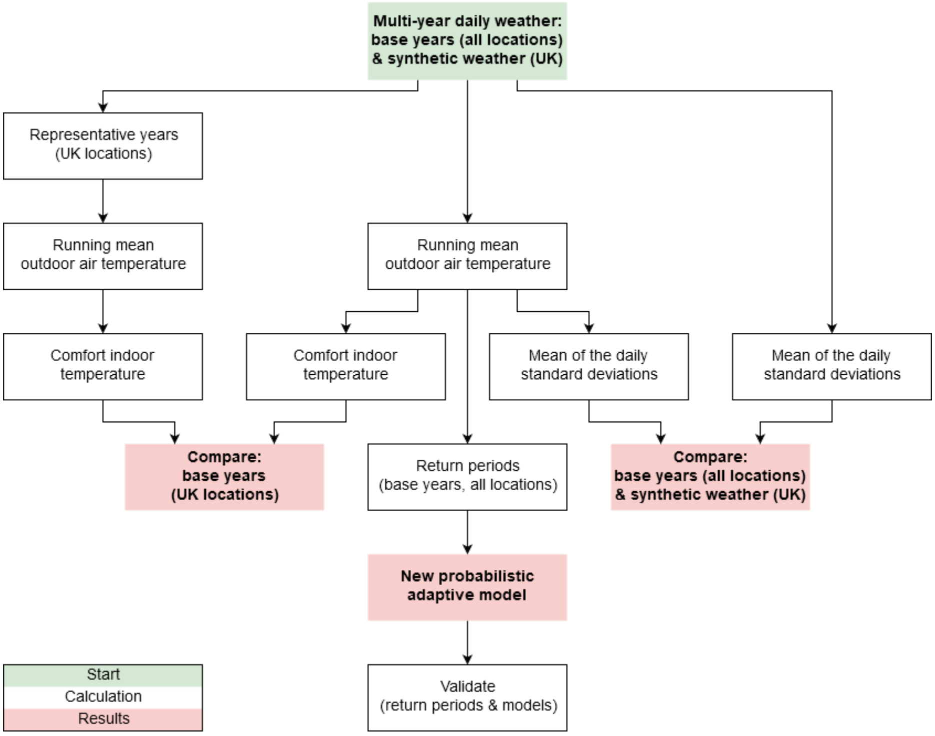


Figure 3: Method workflow. Locations are Ceará, Helsinki, Nuuk, Riyadh, Sydney, Edinburgh*, London* and Manchester*. The UK locations (*) include both historical weather and synthetic weather from the Weather Generator.

4. Calculations and Results

In the following we show the variability of the studied historical weather time series and we introduce and validate a new probabilistic adaptive comfort theory.

4.1. Weather variability

Figure 4 shows the daily mean outdoor temperature record for London over 22 base years, together with two common reference years (TRY and DSY). It is clear that for this Köppen Class C location, there is a large year-on-year variation in the temperature, with some winter days being almost as warm as some summer days. Converting these time series to upper and lower allowable indoor temperature limits using equations (1) to (3) gives Figure 5, from which it is seen that the variability in both the upper and lower bound reaches up to 3.5°C, i.e. almost half the 7°C that the adaptive comfort model gives for the distance between the bounds, and equal to the distance between the comfort temperature, given by equation (4), and the bounds.

Repeating this analysis for the other locations shows similar results (Figure 6), however it is clear that the inter-year range found depends greatly on the location — implying that in some locations the potential error created by using a single representative year will be greater than in others.

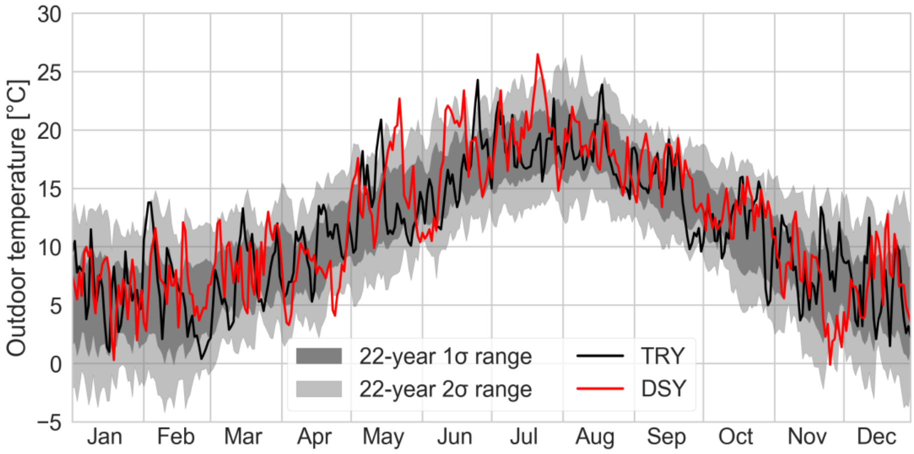


Figure 4: Daily mean outdoor temperatures for London (22 base years). The shaded areas indicate 1 and 2 standard deviations (σ) of the daily mean outdoor temperatures.

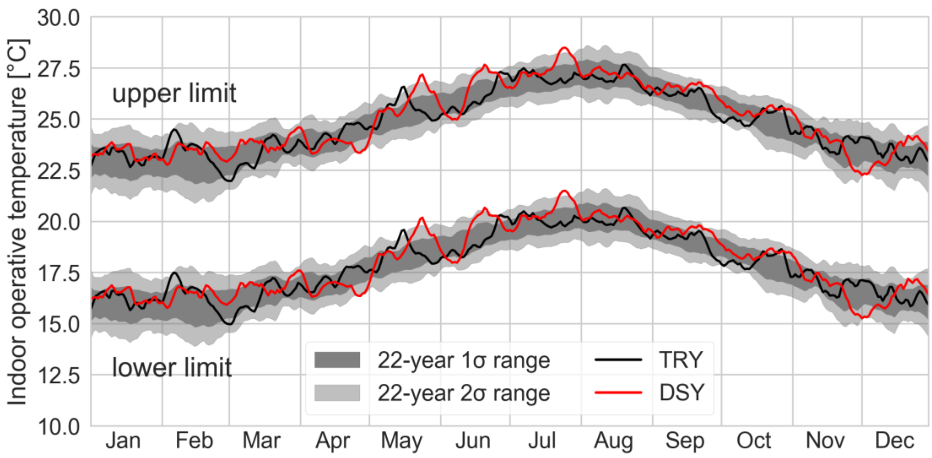
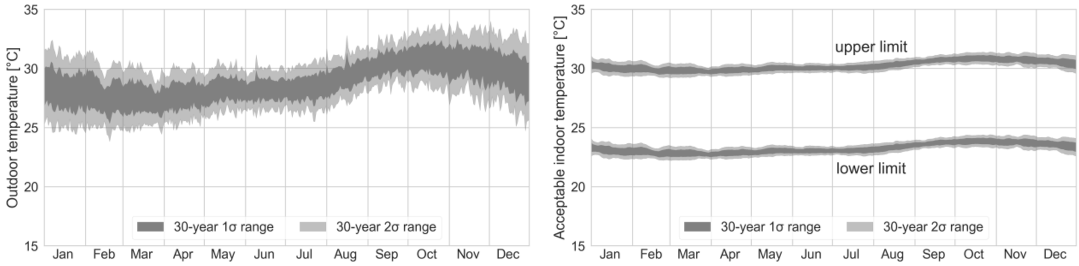
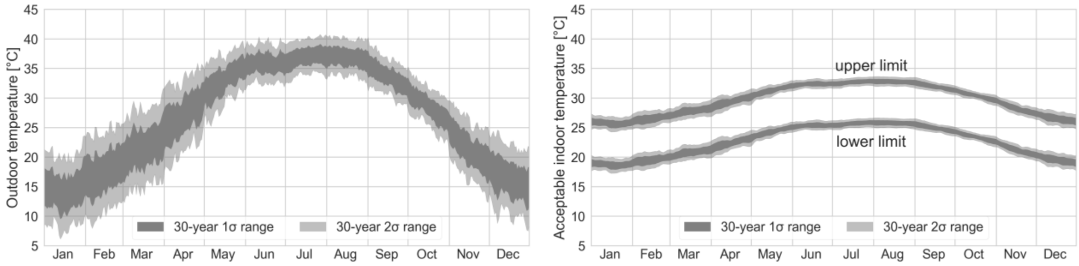


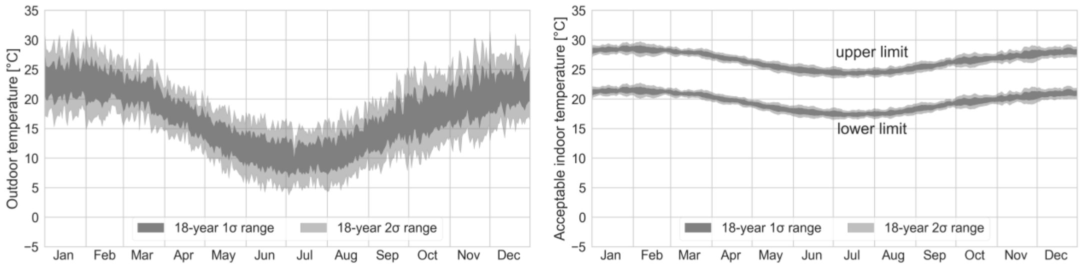
Figure 5: Upper and lower bounds of acceptable indoor temperatures for London (22 base years), derived from equations (1) to (3). The comfort bounds extend outside the 10 to 33.5°C running mean temperature range implied by the adaptive comfort theory. The shaded areas indicate 1 and 2 standard deviations (σ) of the daily acceptable indoor operative temperatures.



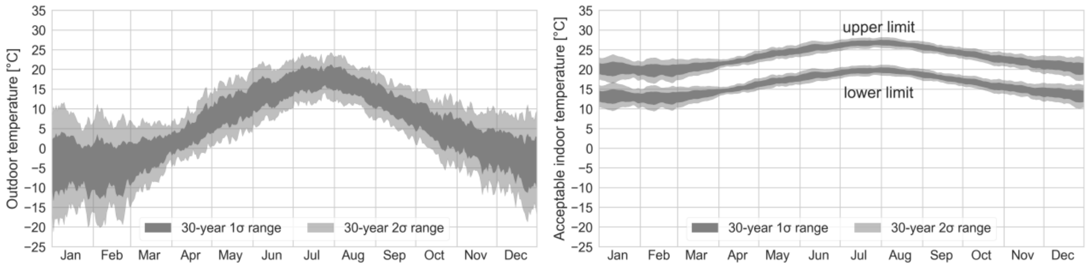
Ceará, Brazil (Köppen A)



Riyadh, Saudi Arabia (Köppen B)

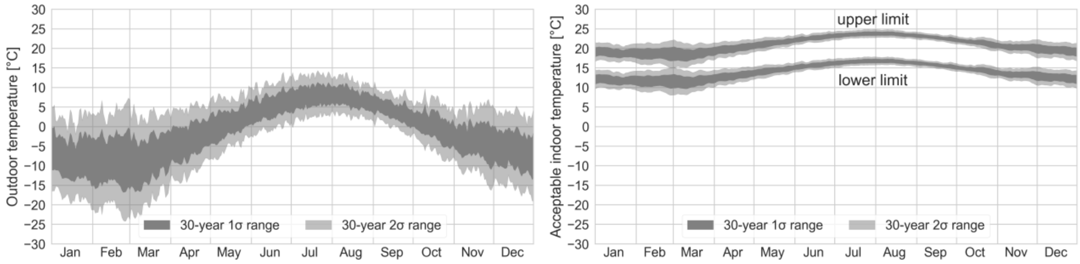


Sydney, Australia (Köppen C)



Helsinki, Finland (Köppen D)

10



Nuuk, Greenland (Köppen E)

Figure 6: Daily mean outdoor temperatures (left in each pair) and acceptable indoor temperatures (right in each pair) for the study locations. The comfort bounds extend outside the 10 to 33.5°C running mean temperature range implied by the adaptive comfort theory. The shaded areas indicate 1 and 2 standard deviations (σ) of the daily mean temperatures.

Table 1 shows the spread in the source data and the spread after application of equation (3) for 3 locations in UK (London, Edinburgh and Manchester). This is represented as the mean of the daily standard deviations of the mean temperatures calculated both over all the mean daily temperatures ($\sigma_{day,Tout}$) and only over the restricted 10 to 33.5°C range implied by the adaptive comfort theory ($\sigma_{day,res,Tout}$). $\sigma_{day,Trm}$ and $\sigma_{day,res,Trm}$ are the equivalent quantities calculated using the running mean given by equation (3). The main logic for calculating the restricted standard deviation is that the model is to be used over the 10 to 33.5°C running mean temperature range where it is considered valid. This has also the advantage of being a more robust statistical indicator since the extreme periods, if present, are discarded.

Although it would be possible to calculate return periods for the data shown in Figures 5 and 6, they have the potential to be poor estimates for use as the basis of return periods, as relatively few years of data are available. We therefore need to obtain an estimate of how reliable any these standard deviations are by using a longer time series. The weather generator was therefore used to create 3,000 years of synthetic weather for London, Edinburgh and Manchester in the UK. $\sigma_{day,Tout}$, $\sigma_{day,res,Tout}$, $\sigma_{day,Trm}$ and $\sigma_{day,res,Trm}$ for the 3,000 years of synthetic weather are reported in Table 1.

The data of Table 1 confirms the visual suggestion of Figures 4 and 5, i.e. that the variability in the temperatures is substantial. It also confirms that the standard deviations generated using the base years are good estimates of the true standard deviations, both in terms of the external temperature series T_{out} and running mean temperature T_{rm}.

These results clearly show that under the adaptive comfort theory and a single reference year, it is possible to design buildings which might easily fail in a subsequent year.

Table 1: Variability in the weather data for 3 locations in UK over the 22 base years used to form the reference years, and over the 3,000 synthetic weather years.

	Base years (22 years)				Synthetic weather (3,000 years)			
	$\sigma_{day,Tout}$	$\sigma_{day,res,Tout}$	$\sigma_{day,Trm}$	$\sigma_{day,res,Trm}$	$\sigma_{day,Tout}$	$\sigma_{day,res,Tout}$	$\sigma_{day,Trm}$	$\sigma_{day,res,Trm}$
London	2.88	2.58	1.94	1.77	2.95	2.69	1.99	1.76
Edinburgh	2.91	2.64	2.07	1.94	2.63	2.29	1.74	1.46
Manchester	2.84	2.58	2.30	2.45	2.79	2.53	1.85	1.60

Extracting the standard deviations for the other study locations gives Table 2. Again, the spread is considerable. It is also to be noticed that for locations of Köppen E climate (such as Nuuk in Greenland) there is no spread available for $\sigma_{day,res,Tout}$ and $\sigma_{day,res,Trm}$ as the running mean outdoor temperatures are always outside the range of applicability (10 to 33.5°C) of the adaptive model.

Table 2: Variability in the worldwide weather data.

	Base years (n years)				
	n	$\sigma_{day,Tout}$	$\sigma_{day,res,Tout}$	$\sigma_{day,Trm}$	$\sigma_{day,res,Trm}$
Ceará (Brazil, Köppen A)	30	1.17	1.17	0.79	0.79
Riyadh (Saudi Arabia, Köppen B)	30	2.39	2.78	1.60	1.77
Sydney (Australia, Köppen C)	18	2.67	2.69	1.36	1.37
Helsinki (Finland, Köppen D)	30	3.96	2.97	2.88	2.17
Nuuk (Greenland, Köppen E)	30	3.83	n.a.	2.68	n.a.

4.2. A new probabilistic adaptive comfort equation

The probability for a normally distributed random variable Z with expected value 0 and variance 1 of having a value smaller than z, i.e. $p(Z \leq z)$, is given by the cumulative distribution function $\tau(z)$. To straightforwardly use τ with no need to look up the inverse of the normal distribution we can use the simple approximation based on [39]:

$$z \cong \frac{(p)^{0.135} - (1-p)^{0.135}}{0.1975} \qquad (5)$$

This approximation is valid for the case in which $p \geq 0.5$. Considering a return period N, we find that $p = 1 - \frac{1}{N}$ (i.e. p can be interpreted as the probability of not obtaining a value that is smaller or equal to a one-in-N-year extreme event) and therefore equation (5) becomes equation (6), which correctly covers all the return periods longer than 2 years.

$$z \cong \frac{\left(1-\frac{1}{N}\right)^{0.135} - \left(\frac{1}{N}\right)^{0.135}}{0.1975} \tag{6}$$

Given a reliable estimate of $\sigma_{day,res,Trm}$ we can then calculate the excursion for any return period as $z(N) \cdot \sigma_{day,res,Trm}(K)$. This excursion is the ΔT required to adjust the model to make a building resilient to a one-in-N-year extreme event in a given location (K). Table 3 shows examples for these excursions. In addition, we can create a new probabilistic thermal comfort model based on the following equations:

$$T_{upper,N} = (0.31 \cdot Tout + 17.8) + 3.5 - z(N) \cdot \sigma(K), \quad \text{and} \tag{7}$$
$$T_{lower,N} = (0.31 \cdot Tout + 17.8) - 3.5 + z(N) \cdot \sigma(K) \tag{8}$$

where, as before, T_{out} is given by equation (4), σ depends on the climate K where the building is located and z depends on the selected return period N. Ideally K would be fully localized, however, as these are standard deviations, not means, the values given in Table 3 can be used as approximations over all locations of identical Köppen classification.

Table 3: Excursions for a range of return periods for the locations studied (i.e. values for $\Delta T = z(N) \cdot \sigma(K)$ in equations (7) and (8)).

	Excursion ΔT (°C)			
Return period N (years) / Location	5	10	25	100
Ceará (Brazil, Köppen A)	0.66	1.01	1.39	1.85
Riyadh (Saudi Arabia, Köppen B)	1.48	2.27	3.11	4.14
Sydney (Australia, Köppen C)	1.15	1.76	2.41	3.20
Helsinki (Finland, Köppen D)	1.82	2.78	3.81	5.07
Nuuk (Greenland, Köppen E)	n.a.	n.a.	n.a.	n.a.
London, (UK, Köppen C)	1.48	2.27	3.11	4.14

Plotting equations (7) and (8) we have a probabilistic chart similar to that of Figure 1, but this time with upper and lower limits defined by a series of the probabilistic lines, in this case shown for N = 5 (Figure 7).

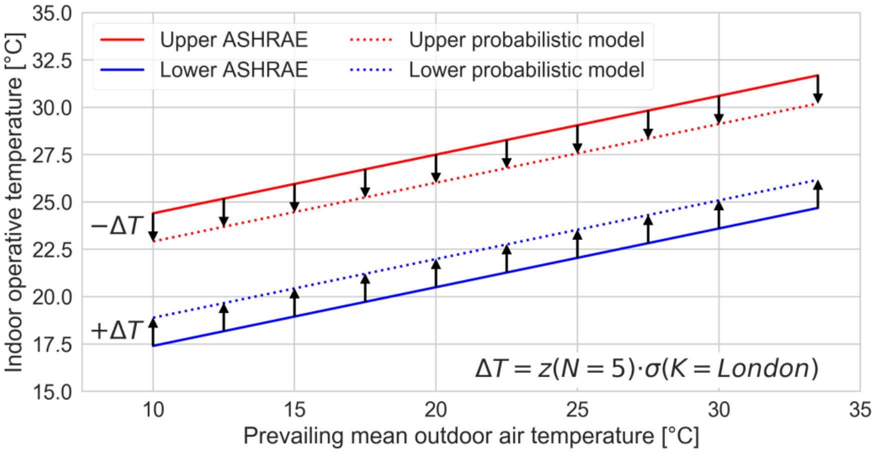


Figure 7: Probabilistic adaptive thermal comfort limits for London, from equations (7) and (8). The location of the return period lines is climate dependent.

4.3. Validation

Validation requires two steps: (1) looking at the return periods, (2) looking at the excursions above the comfort line for a building. The return period estimates are based on the standard deviations, and although in the above we have shown that σ from the weather generator is similar to σ from the 22 base years, this does not show that is correct, particularly over the number of standard deviations needed for large return periods.

The Central England Temperature Record spans 358 years, from 1659 to today (daily since 1772). A Shapiro-Wilk normality test [40] based on the annualised mean daily temperature[1] within the record gives W = 0.995 and p-value = 0.237, thereby providing no evidence to reject the normality of the data (as p-value >> 0.05). For this data, the values shown in Table 4 are obtained; these are very similar to those from the 22 base years for London and the weather generator. So the standard deviations reported earlier would seem to be reasonable, validating the return periods.

Table 4: Variability in the Central England Temperature Record.

	$\sigma_{day,Tout}$	$\sigma_{day,res,Tout}$	$\sigma_{day,Trm}$	$\sigma_{day,res,Trm}$
Central England Temperature Record (358 years)	2.77	2.33	1.88	1.57

To validate the predicted excursions, and demonstrate the method, the number of hours that a building subjected to a one-in-N-year weather breaches the upper comfort equation in the ASHRAE model (1) is compared to the number of hours a building subjected to a reference year breaches the one-in-N-year probabilistic upper comfort equation (5). Figure 8 shows this for London with N=100 and σ=1.76 (WG simulations: 100th percentile (1-in-100 risk) and 50th percentile (average case, 50-in-100 risk). The data again came from the weather generator, but this time with a high carbon emission scenario and for the 2080s, thereby

[1] Normality tests are unsuitable for large datasets and 358 years of daily temperatures represent more than 130,000 values. To apply the normality test they have been reduced to 358 values by computing annual means.

ensuring temperatures above the upper threshold. The one-in-100-year has 3,529 hours above the normal comfort line; the reference year has a similar 4,117 hours above the one-in-100-year probabilistic comfort line, validating the method.

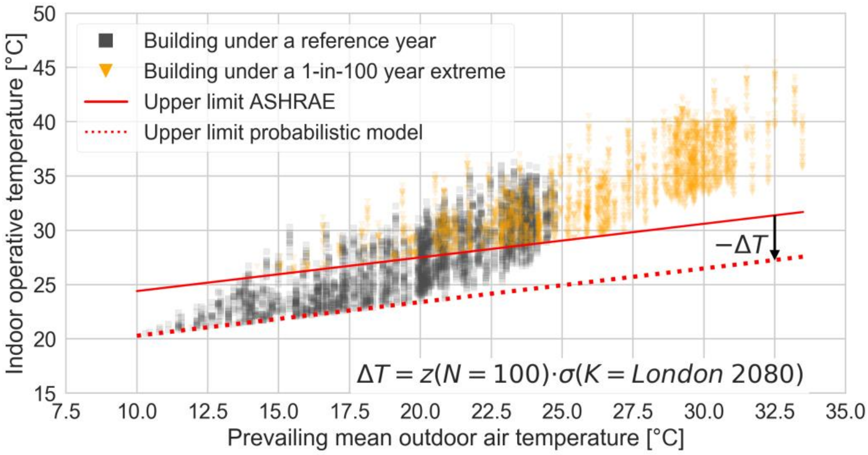


Figure 8: Validation of the method by the comparison of the excursions given by a one-in-100-year year above the normal comfort upper limit line, and the excursions of the reference year above the one-in-100-year probabilistic comfort line. Each dot represents one hour of weather data from either weather files.

5. Discussion

With our new method we can define how sensitive the building or occupants are to a warmer or cooler than average year. For example, an office might be considered robust, with the potential to send occupants home, so a designer might chose to design to be resilient to a one-in-five year, so N=5. Whereas a care home might chose to be far more cautious and desire to be resilient to a one-in-one-hundred-year event, giving N=100. This number is used to define the probabilistic upper or lower line of Figure 7, together with the standard deviation found by using the weather data available at the location in question, as in Table 1 and 2. The results from any design simulation are then compared to this line, and the design altered so that all hours, or not more than a pre-specified number of hours, are above or below the probabilistic line. Considering the case in which our design is specifically addressing an overheating issue, the upper limit should be used. In case of undercooling, the lower limit is to be considered instead.

Our analysis shows that the year-on-year weather variability depends greatly on the location. This implies that in some locations the potential error created by using a single representative year will be greater than in others. Our new probabilistic method is able to take into account this weather variability and promote a resilient building design in any location.

One advantage of this new probabilistic method over the use of multiple probabilistic years for design is that, by retaining the single reference year, all simulations reported to the client, regulatory bodies and other members of the design team are consistent, and based on a single weather file well known to all; whereas, if different weather files are used to represent different return periods, then it is difficult to obtain temporarily consistent simulation results. Another advantage is that it requires only one run of the simulation engine.

6. Conclusions

This paper asks if the natural variability in weather is of such a scale that the academic and practicing engineering community should switch from using a single representative year when applying an adaptive thermal comfort theoretic approach, as is commonly used with naturally ventilated buildings, to a probabilistic one.

For one location in each of the five major Köppen climate classifications and three locations in the UK, observed historical weather files were collated and used to create multi-year adaptive thermal comfort temperature time series. Despite these containing (by definition) a smoothing of the weather data, these new time series showed great variability, demonstrating years when the upper bound in winter was higher than in summer. Then, by using a state-of-the-art validated weather generator, 3,000 years of synthetic weather data was created for the three locations in the UK and the variability in these was shown to match that of the base years used to form common reference years. From this, return periods were found for excursions of the running mean temperatures. This then allowed a new *probabilistic* comfort model to be developed.

In this new probabilistic adaptive comfort theoretic approach, a building is seen to fail not when its internal conditions lie outside the fixed comfort bounds when simulated with a representative year, but when it exceeds the N-year comfort bounds, with N being set by regulation, or dictated by the situation. For example, a hospital or care home might be expected to not breach the bounds more than once in fifty or more years; whereas it might be reasonable to allow a retail complex to be designed against a one-in-five-year limit.

Given the deaths of 14,000 people in Paris in the 2003 heat wave, mainly in naturally ventilated buildings, the additional resilience that the adoption of this approach would give is highly important. Further pertinence is provided by concerns over likely increases in mortality and morbidity in buildings due to a rapidly warming climate.

Acknowledgements

This research forms part of the project COLBE (The Creation of Localized and Future Weather for the Build Environment) funded by the EPSRC (EP/M021890/1) and of the project HHftD (Healthy housing for the Displaced) also funded by the EPSRC (EP/P029175/1). Daniel Fosas and Marika Vellei appreciate the support of the EPSRC 'dCarb' centre (EP/L016869/1). Daniel Fosas is also funded by 'laCaixa' Foundation. All data created during this research are openly available from the University of Bath data archive at https://doi.org/10.15125/BATH-00369.

Bibliography

1. Nicol, J.F. and M.A. Humphreys, *Thermal comfort as part of a self-regulating system.* Building Research and Practice, 1973. **1**(3): p. 174-179.
2. de Dear, R.J. and G.S. Brager. *Developing an adaptive model of thermal comfort and preference*. in *ASHRAE Transactions*. 1998.
3. ASHRAE, *ANSI/ASHRAE Standard 55-2013, Thermal environmental conditions for human occupancy*. 2013: Atlanta, Ga.
4. EN-15251, *Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics*. 2007.

5. Hémon, D. and E. Jougla, *The heat wave in France in August 2003.* Revue d'Epidemiologie et de Sante Publique, 2004. **52**(1): p. 3-5.
6. IPCC, *Summary for Policymakers. In: Climate Change 2013: The Physical Science Basis.* 2013, Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. : Cambridge, United Kingdom and New York, NY, USA.
7. Jones, G.S., P.A. Stott, and N. Christidis, *Human contribution to rapidly increasing frequency of very warm Northern Hemisphere summers.* Journal of Geophysical Research: Atmospheres, 2008. **113**(D2): p. n/a-n/a.
8. Meehl, G.A. and C. Tebaldi, *More Intense, More Frequent, and Longer Lasting Heat Waves in the 21st Century.* Science, 2004. **305**(5686): p. 994-997.
9. Murphy, J.M., et al., *UK Climate Projections Science Report: Climate Change Projections*. 2009, Met Office, Hadley Centre, Exeter.
10. Kingsley, S.L., et al., *Current and projected heat-related morbidity and mortality in Rhode Island.* Environmental Health Perspectives, 2016. **124**(4): p. 460-467.
11. Méndez-Lázaro, P.A., et al., *Climate change, heat, and mortality in the tropical urban area of San Juan, Puerto Rico.* International Journal of Biometeorology, 2016: p. 1-9.
12. D'Ippoliti, D., et al., *The impact of heat waves on mortality in 9 European cities: Results from the EuroHEAT project.* Environmental Health: A Global Access Science Source, 2010. **9**(1).
13. Kottek, M., Grieser, J. , Beck, C., Rudolf, B. and Rubel, F., *World Map of the Köppen-Geiger climate classification updated.* Meteorologische Zeitschrift, 2006. **15**(3): p. 259-263.
14. Eames, M.E., A.P. Ramallo-Gonzalez, and M.J. Wood, *An update of the UK's test reference year: The implications of a revised climate on building design.* Building Services Engineering Research and Technology, 2015. **37**(3): p. 316-333.
15. Herrera, M., et al., *A Review of current and future weather data for building simulation.* Building Services Engineering Research and Technology, 2017.
16. Levermore, G.J. and J.B. Parkinson, *Analyses and algorithms for new Test Reference Years and Design Summer Years for the UK.* Building Services Engineering Research and Technology, 2006. **27**(4): p. 311-325.
17. Jentsch, M.F., et al., *Limitations of the CIBSE design summer year approach for delivering representative near-extreme summer weather conditions.* Building Services Engineering Research and Technology, 2013. **35**(2): p. 155-169.
18. Liu, C., et al., *Future probabilistic hot summer years for overheating risk assessments.* Building and Environment, 2016. **105**: p. 56-68.
19. Belcher, S.E., J.N. Hacker, and D.S. Powell, *Constructing design weather data for future climates.* Building Services Engineering Research and Technology, 2005. **26**(1): p. 49-61.
20. Eames, M., T. Kershaw, and D. Coley, *A comparison of future weather created from morphed observed weather and created by a weather generator.* Building and Environment, 2012. **56**: p. 252-264.
21. Kočí, J., J. Maděra, and R. Černý, *Generation of a critical weather year for hygrothermal simulations using partial weather data sets.* Building and Environment, 2014. **76**: p. 54-61.
22. Cox, R.A., et al., *Simple future weather files for estimating heating and cooling demand.* Building and Environment, 2015. **83**: p. 104-114.
23. Taylor, J., et al., *The relative importance of input weather data for indoor overheating risk assessment in dwellings.* Building and Environment, 2014. **76**: p. 81-91.

24. Nicol, J.F., et al., *Suggestion for new approach to overheating diagnostics.* Building Research & Information, 2009. **37**(4): p. 348-357.
25. Eames, M., *An update of the UK's design summer years: Probabilistic design summer years for enhanced overheating risk analysis in building design.* Building Services Engineering Research and Technology, 2016.
26. Watkins, R., G. Levermore, and J. Parkinson, *The design reference year - a new approach to testing a building in more extreme weather using UKCP09 projections.* Building Services Engineering Research and Technology, 2012. **34**(2): p. 165-176.
27. Smith, S.T. and V. Hanby, *Methodologies for the generation of design summer years for building energy simulation using UKCP09 probabilistic climate projections.* Building Services Engineering Research and Technology, 2012. **33**(1): p. 9-17.
28. Jentsch, M.F., M.E. Eames, and G.J. Levermore, *Generating near-extreme Summer Reference Years for building performance simulation.* Building Services Engineering Research and Technology, 2015. **36**: p. 701-727.
29. Jentsch, M.F., et al., *Limitations of the CIBSE design summer year approach for delivering representative near-extreme summer weather conditions.* Building Services Engineering Research and Technology, 2013. **35**: p. 155-169.
30. Nicol, J.F. and M.A. Humphreys, *Adaptive thermal comfort and sustainable thermal standards for buildings.* Energy and Buildings, 2002. **34**(6): p. 563-572.
31. Yao, Y., et al., *Experimental study on physiological responses and thermal comfort under various ambient temperatures.* Physiology & Behavior, 2008. **93**(1–2): p. 310-321.
32. Lee, J.-Y., et al., *Cutaneous Warm and Cool Sensation Thresholds and the Inter-threshold Zone in Malaysian and Japanese Males.* Journal of Thermal Biology, 2010. **35**(2): p. 70-76.
33. Lichtenbelt, W.V.V.M., *To comfort or not to comfort?*, in *International Conference of Healthy Buildings Europe*. 2015: The Netherlands.
34. Halawa, E. and J. van Hoof, *The adaptive approach to thermal comfort: A critical overview.* Energy and Buildings, 2012. **51**(0): p. 101-110.
35. MetOffice, *Met Office Integrated Data Archive System (MIDAS) Land and Marine Surface Stations Data (1853-current)*. 2012, NCAS British Atmospheric Data Centre.
36. UKCP09. *UK Climate Projections (UKCP09)* Available from: http://ukclimateprojections.metoffice.gov.uk/21809.
37. IPCC, *Climate Change 2014: Synthesis Report*. 2014: Geneva, Switzerland.
38. Manley, G., *Central England temperatures: Monthly means 1659 to 1973.* Quarterly Journal of the Royal Meteorological Society, 1974. **100**(425): p. 389-405.
39. Shore, H., *Simple Approximations for the Inverse Cumulative Function, the Density Function and the Loss Integral of the Normal Distribution.* Journal of the Royal Statistical Society. Series C (Applied Statistics), 1982. **31**(2): p. 108-114.
40. Shapiro, S.S. and M.B. Wilk, *An analysis of variance test for normality (complete samples)†.* Biometrika, 1965. **52**(3-4): p. 591-611.

Appendix

A field study of indoor thermal comfort in Colombia

This study reports results of a field study conducted in Bogotá by a master student of the Department of Architecture and Civil Engineering at the University of Bath.

In this study, indoor thermal comfort is investigated in three different free-running offices (naturally ventilated, mechanical ventilated and mixed-mode) in Colombia. Fanger's PMV/PPD model is found to sufficiently describe thermal conditions in the free-running mechanical ventilated and mixed-mode offices, but not in the naturally ventilated office. The reduced availability of personal control over the windows in the two surveyed naturally ventilated and mixed-mode free-running offices invalidates adaptive model predictions. These findings provide evidence that the lack of control in naturally ventilated buildings strongly reduces occupant thermal comfort and hence invalidates adaptive model predictions.

This work is totally based on a same-titled paper published in the Journal of Building Engineering in 2015, more details are provided below.

Declaration of Authorship

<table>
<tr><td colspan="2">This declaration concerns the article entitled:

A field study of indoor thermal comfort in the subtropical highland climate of Bogotá, Colombia</td></tr>
<tr><td>Status</td><td>Published in the Journal of Building Engineering.</td></tr>
<tr><td>Details</td><td>Sukumar Natarajan, Juan Rodriguez & Marika Vellei, A field study of indoor thermal comfort in the subtropical highland climate of Bogotá, Colombia, Journal of Building Engineering, 2015, Volume 4, Pages 237-246.
DOI: doi.org/10.1016/j.jobe.2015.10.003</td></tr>
<tr><td>Authors' contribution</td><td>The author of this thesis contributed to the statistical analysis of the data (50%) and to the preparation of the manuscript (30%). Each author's exact contribution to the article is outlined below:
S. Natarajan: Formulation of ideas (50%), Design of methodology (50%), Preparation of the manuscript (30%).
J. Rodriguez: Collection of data (100%), Formulation of ideas (50%), Design of methodology (50%), Processing/Analysis of data (50%), Preparation of the manuscript (30%).
M. Vellei: Processing/Analysis of data (50%), Preparation of the manuscript (40%).</td></tr>
<tr><td>Statement from Candidate</td><td>This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.</td></tr>
<tr><td>Date and Signature</td><td></td></tr>
</table>

A field study of indoor thermal comfort in the subtropical highland climate of Bogota, Colombia

Sukumar Natarajan[a, b], Juan Rodriguez[a], Marika Vellei[a]

[a] *Department of Architecture and Civil Engineering, University of Bath, Bath, UK*
[b] *Corresponding author. Room: 6E 2.23. Claverton Down Road, BA2 7AY, UK Bath. Tel: +44 (0) 1225 386358. Email: s.natarajan@bath.ac.uk*

Keywords: PMV/PPD, adaptive approach, mixed-mode ventilation, subtropical highland climate

Nomenclature

Cll 72-NV	naturally ventilated office
Cll 93-MV	mechanically ventilated office
Cll 100-MM	mixed-mode office

ABSTRACT

This paper undertakes the first field study of indoor thermal comfort in Colombia. The objective of this study was to compare thermal comfort data gathered in office buildings in Bogota, Colombia with the predictions made by three well established standards: ISO 7730:2005 (PMV model), ANSI/ASHRAE Standard 55:2013 (adaptive model) and EN Standard 15251 (adaptive model). The study comprised the administration of a thermal assessment survey to 115 participants and the simultaneous measurement of indoor and outdoor physical variables in 3 offices having different ventilation regimes (natural ventilation, mechanical ventilation and mixed-mode i.e. both natural ventilation and air-conditioning). The findings show that the PMV model incorporated in the ISO 7730 as well as in the ASHRAE standard (which is the standard currently adopted in Colombia for regulating indoor environmental parameters) is able to describe comfort conditions in the mechanically ventilated (MV) office. In the case of the naturally ventilated office (NV), results indicate that the PMV model is not successful at estimating occupants' thermal sensations, and underestimates occupants' perception of discomfort. The EN 15251 adaptive model underestimates thermal discomfort in the NV and MM offices. The ASHRAE adaptive model shows similar patterns underestimating discomfort in the NV office. The findings provide robust evidence that the lack of perceived or actual control in low-energy naturally ventilated buildings strongly reduce occupants' thermal comfort and thus invalidate adaptive model predictions.

1. Introduction

Human thermal comfort has been a subject of research for more than a century, in parallel to the ever more prevalent role of air-conditioning in the market [1]. That research has produced significant findings and developments and has led to the advent of standardisation. Thermal comfort standards have been established in order to allow the measurement and evaluation of those thermal environments humans are usually exposed to [2].

In the late 1960s, P.O. Fanger, pioneer of the thermal comfort research, created a static heat-balance model with the aim of defining a referenced set of indoor environmental variables which were able to provide acceptable thermal conditions to the majority of the occupants [3, 4]. Fanger's model led to the definition of the well known PMV (Predicted Mean Vote) and PPD (Predicted Percentage of Dissatisfied) indices which were firstly incorporated into the ISO international standard in 1984.

However, Fanger's model was only intended for application in artificially controlled spaces; the problem of defining thermal comfort conditions in naturally ventilated environments has led to the conceptualization of the adaptive model of thermal comfort which was firstly introduced by Nicol and Humphreys in the 1970s [5] and, then, incorporated in 2004 into the ASHRAE Standard 55 thanks to the research of Brager and De dear [6].
The evidence underpinning those models has been obtained either in climate chambers (Fanger' conventional model) or in actual buildings (adaptive models). Fanger's model is based on experiments conducted in climate chambers in Denmark and the United states [4]. The adaptive model of the ASHRAE Standard 55 is based on data collected in the 1990s by de Dear and Brager as part of the ASHRAE Project RP-884 [6] involving field measurements in Thailand, Indonesia, Singapore, Pakistan, Greece, UK, USA, Canada and Australia. The adaptive model described by Nicol and Humphreys (EN Standard 15251) is based on data collected in the EU Project Smart Controls and Thermal Comfort (SCATs) [7] which involved a 3-years survey of 26 European buildings in France, Greece, Portugal, Sweden and the UK.
Therefore, despite being termed international standards, these standards are based on data from a limited number of geographical regions of the world focusing on Europe, North America, Asia and Australia.
Field studies are fundamental for assessing existing comfort standards in other regions of the world and for developing new algorithms defining comfort conditions in different climates and cultures. The assessment of the applicability of thermal comfort standards requires field data comprising both objective sensor data (air temperature, globe temperature, relative humidity and air speed) and subjective data (actual thermal sensations recorded at the same time as the objective data, thermal preferences etc.).
This paper intends to compare thermal comfort data gathered in a field study in Bogota, Colombia with the comfort predictions and temperature values recommended and regarded as universal by the international comfort standards ISO 7730:2005 [2], ASHRAE Standard 55-2013 [8] and EN Standard 15251 [9].

1.1 Bogota's climatic characteristics

Bogota's local climate is influenced by two key factors: its latitude and its elevation. Bogota's elevation is 2600 m above sea level. It is well known that there is a clear correlation between elevation and average annual temperatures. For this reason, although tropical latitudes are usually associated with tropical climates which are characterized by a lowest mean monthly air temperature never under 18°C [10], the annual average temperature in Bogota is only 14.2°C, between a mean minimum of 8.4°C and a mean maximum of 19.7°C [11]; the region has a subtropical highland climate which is oceanic rather than tropical. The Köppen-Geiger climate classification for Bogota is Cfb [10].
Studies have shown that cognitive and affective expectations - as identified by de Dear [1] - are not take into account in chamber studies [3]. For that reason, field studies of the same populations have shown consistent differences in relation to the comfort temperatures predicted by the Fanger's heat-balance model [1, 12-14]. It has been even suggested that the tropics might require a different level of comfort consideration from that currently provided in the standards [15]. In consequence, existing literature not only indicates that there is room for expanding the study of thermal comfort in tropical regions, but also highlights the fact that not enough internationally-recognised research has been done in the tropical zone of the Americas [16].
Furthermore, the particular climatic conditions of Bogota (which belongs to a tropical area but experiences a subtropical highland climate) are very different than those usually experienced in tropical latitudes. Bogota's climate is characterized by narrow variations of

annual temperatures and precipitations distributed all year around, which are typical features of oceanic climates [10]. Therefore, the study of thermal comfort conditions in Bogota is of particular interest for three main reasons:

- to the authors' knowledge, no previous thermal comfort study has been carried out for this type of climate;
- the similarity with an oceanic climate makes extremely interesting to assess if international standards can be applied;
- the benefits of the knowledge that a study on this matter could bring, are not circumscribed to the particular interest of Bogota, but would suit also other cities under the same climatic conditions (subtropical highland climate); for example Pasto and Tunja (regional capitals in Colombia), Quito and Cuenca (national and regional capital respectively, in Ecuador), and Cajamarca (regional capital in Peru). This could potentially help to inform building codes in these countries.

1.2 Colombia's background

The existing building code in Colombia mainly deals with the suitability of the structural response of a building to seismic forces and incorporates some regulations related to fire protection [17]. Thermal comfort in buildings is only regulated by the Standard NTC 5316 [18] which is a Spanish translation of the ANSI/ASHRAE Standard 55. As outlined before, the ANSI/ASHRAE Standard 55 is based on studies from a limited number of geographical regions of the world focusing on Europe, North America, Asia and Australia and, therefore, could fail in predicting neutral temperatures in Colombia; this could consequently affect the need and the design of AC systems leading to higher energy consumptions and obvious environmental issues. Furthermore, the ANSI/ASHRAE Standard 55 categorizes mixed-mode buildings into the air-conditioned group (i.e. under the PMV model) and limits the applicability of the adaptive model to strictly naturally ventilated buildings without mechanical cooling system installed, therefore it is interesting to verify if the adaptive model is also applicable for these "special" mixed-mode buildings which have the potential to reduce energy consumption for cooling [19].

From the adaptive model proposed by ASHRAE, the acceptable operative temperature range for a naturally conditioned space under a mean monthly outdoor temperature of 14.2°C (which is the annual average temperature in Bogota) would be between 18.7°C and 25.7°C for a 80% acceptability (see Figure 1) [8]. Since the temperature in Bogota varies between a mean minimum of 8.4°C and a mean maximum of 19.7°C, the temperature range 18.7°C-25.7°C is easily maintainable inside buildings. This could partially explain the absence of widespread heating or cooling systems in buildings in Bogota. Consequently, it could be argued that a sensible approach to passive design has the potential to produce a thermally comfortable indoor environment without the need of additional conditioning.

Concerns about climate change are also important drivers in relation to research in thermal comfort. Models presented by the Government of Colombia show that temperatures in Bogota could increase between 2°C and 4°C by the end of the century [20], which would be directly linked to conditions inside buildings and therefore to potential increases in energy consumption.

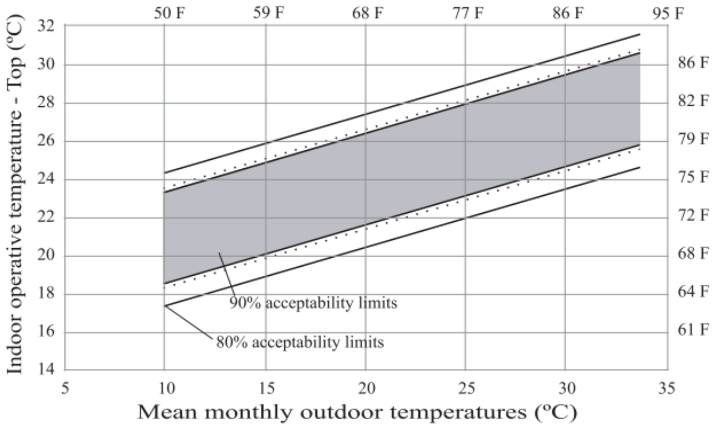


Figure 1 Acceptable operative temperature ranges for naturally conditioned spaces according to the adaptive model proposed by ANSI/ASHRAE Standard 55:2013.

2. Methodology

2.1 Characteristics of the selected offices

The survey was conducted between the 5th and 12th of August 2011, as a cross sectional data collection in three offices in three different buildings in Bogota. The criteria for selection of the offices were:

- their main ventilation strategies had to be different;
- the occupants' level of activity in all of them had to be similar.

All the selected buildings are situated in the same area of Bogota and all the offices belong to the same company, which provides some degree of similarity in terms of layout, materials, furniture, level of activity and dress code. In all the three offices occupants are allowed to adapt their clothing level. A short description of the three selected offices is reported below:

- Office Building Calle 72 (Cll 72-NV): it is the oldest building of the group, built around 30 years ago. Its façade is a combination of masonry and single glazing. The existing ventilation scheme is based completely on ventilation driven by natural forces (NV) without mechanical cooling system.
- Office Building Calle 93 (Cll 93-MV): this building was constructed 15 years ago. Its façade is single-glazed and although it has some operable windows, the main ventilation scheme in this office is through mechanical ventilation (MV) without mechanical cooling system.
- Office Building Calle 100 (Cll 100-MM): the most recent building, it was finished in 2007. It has mostly a single-glazed façade with masonry frames. Although there was an environmental engineer in the team for ensuring the sustainable design of the building, the office had to finally rely on an air-conditioning system (AC) for ventilation and thermal comfort. However, a part of the building (which includes the surveyed office) is equipped with operable windows and, therefore, can run in free-mode when natural ventilation is sufficient to provide acceptable environmental conditions (i.e. room air temperature lower than 27°C). The surveyed office (mixed-mode office) is free-running during the survey period.

The characteristics of the three buildings support the idea of traditional avoidance of artificial conditioning, but they also highlight the recent tendency to increase the level of thermal control by introducing air-conditioning [21].

Figure 2 Location and photos of the selected buildings (map adapted from Google Maps).

2.2 Distribution of the sample

Each office provided between 35 and 40 data sets for a total of 115 respondents: in Cll 72-NV a total of 40 occupants took part, Cll 93-MV provided 37 questionnaires and Cll 100-MM had 38 participants. Apart from selecting subjects that had the same apparent level of activity (office work), there was no other differentiation or specific targeting in relation to those filling in the questionnaire. Participation was only dependant on the willingness and availability of the workers present at the time of the visits.

Table 1 Distribution of participants by gender.

	No of persons		% of females	
	Overall	**Sample**	**Overall**	**Sample**
Cll 72-NV	54	40 (74%)	67%	63%
Cll 93-MV	61	37 (61%)	62%	65%
Cll 100-MM	60	38 (63%)	65%	71%

Most of the subjects surveyed were between 21 and 50 years old (94%). Nearly 85% of the surveyed population had lived in Bogota more than 15 years, but more remarkable is the fact that 97% of the sample had lived there more than 5 years and none less than one year. These figures safely lead to state that the whole sample can be regarded as naturally acclimatised to the climatic conditions of Bogota [22].

Table 1 compares the demographics of the obtained sample against the overall population in each office. The obtained samples represent more than 60% of the total occupants in each office.

2.3 Questionnaire

The questionnaire was created following the indications given in ASHRAE [8] and ISO 7730 [2] and based on the survey already developed by Cena and de Dear [22]. It included the following information:

- Thermal sensation vote (TSV), measured on the seven-point Likert scale used both in the ASHRAE and ISO standards. Participants could report votes along a continuous scale from -3 to 3 (cold: -3, cool: -2, slightly cool: -1, neutral: 0, slightly warm: 1, warm: 2, hot: 3).
- Comfort vote, intended to record occupants' judgement in relation to the existing thermal load. It proposed one pole (comfortable) and four degrees of discomfort to choose from (slightly uncomfortable, uncomfortable, very uncomfortable and extremely uncomfortable).
- Thermal preference vote (TPV), reported in the scale: much cooler, a bit cooler, no change, a bit warmer, much warmer.
- Thermal acceptability vote (TAV) reported in the scale: generally acceptable, generally unacceptable.
- Perceived level of control over the thermal environment and air quality. Occupants had five different options to choose from: no control, light control, medium control, high control, total control.
- Control strategies used. Occupants had to indicate if the following strategies were present and, if so, how often they were used: operating or adjusting windows, exterior doors, interior doors, thermostats, blinds or drapes, local heaters or local fans.
- Current clothing (see Figure 3).
- Activity levels in the previous 30 minutes (see Figure 3).
- Food/beverage intake in the last 15 minutes (see Figure 3).

The questionnaire had to be written in Spanish and apart from some guidelines provided by the mentioned ISO standard, all the questions were a free translation from the English version. Additionally, some minor adjustments had to be made, including for example a scarf in the list of possible garments that composed the clothing ensemble.

What activities have you been engaged in during the preceding hour?

	Sitting quietly	Sitting typing/desk work	Standing still	On your feet working	Walking around
Last 10 minutes?	□	□	□	□	□
The 10 minutes preceding?	□	□	□	□	□
The 10 minutes before that?	□	□	□	□	□
The half hour before that?	□	□	□	□	□

Please indicate whether you have consumed any of the following items within the last 15 minutes

Caffeinated drink	Cold drink	Hot drink	Cigarette	Snack or meal
□	□	□	□	□

Please indicate whether you are wearing any of the items listed below by circulating the appropriate number:
0 = not wearing item / 1 = light weight item / 2 = medium weight item / 3 = heavy weight item

Female				Item	Male			
				Underlayer				
0	1	2	3	Top	0	1	2	3
0	1	2	3	Bottom	0	1	2	3
0	1	2	3	Slip				
				Footwear				
0	1	2	3	Socks	0	1	2	3
0	1	2	3	Shoes	0	1	2	3
0	1	2	3	Pantyhose				
				Midlayer				
0	1	2	3	Short sleeved shirt	0	1	2	3
0	1	2	3	Long sleeved shirt	0	1	2	3
0	1	2	3	Pants	0	1	2	3
0	1	2	3	Shorts	0	1	2	3
0	1	2	3	Dress				
0	1	2	3	Skirt				
				Outerlayers				
0	1	2	3	Sweater	0	1	2	3
0	1	2	3	Vest	0	1	2	3
0	1	2	3	Jacket	0	1	2	3
0	1	2	3	Scarf	0	1	2	3

Figure 3 Questions regarding activity level, food/beverage intake and clothing.

2.4 Instrumentation

From a selection of commercially available instruments, two were selected for the surveys: the HT30 Heat Stress WBGT Meter supplied by Extech Instruments (www.extech.com), and the Hot Wire USB Logging Anemometer supplied by ATP Instrumentation (www.atp-instrumentation.co.uk). Table 2 compares the range and accuracy for each type of measurement against the requirements of ISO 7726:2001 [23]. It can be observed that the required accuracy for air temperature is not met by either instruments. The lower boundary for air velocity measurements has also not been met, though the accuracy is within the required tolerance. This difference does not detract the general findings from their significance, taking into account that the application of the PMV model relies on a number of assumptions (e.g. about the metabolic rate and clothing insulation values, see 2.6) which influence the overall accuracy level. However, these limitations will have to be borne in mind when evaluating the results.

Table 2 Instrumentation details against those specified in ISO 7726:2001.

	Parameter	Range		Accuracy	
		Instrument	**Standard**	**Instrument**	**Standard**
Extech HT30	Black Globe	0 – 80 °C	10 – 40 °C [(1)]	± 2 °C	± 2 °C [(1)]
	Air Temperature	0 – 50 °C	10 – 40 °C	± 1 °C	± 0.5 °C
	Relative Humidity	0 – 100 %	---	± 3 %	---
ATP Hot Wire Anemometer	Air Velocity (v_a)	0.1 – 25 m/s	0.05 – 1 m/s	± 5 %	± (0.05+0.05v_a)
	Air Temperature	0 – 50 °C	10 – 40 °C	± 1 °C	± 0.5 °C

[(1)] requirements for computing mean radiant temperature

2.5 Measurements and calculations

The survey was conducted in each office as a 'point-in-time' survey which means that thermal sensations and physical parameters at each workstation were recorded at the same time. Measurements were carried out from 9 am till about 4:00 pm. Both instruments were fitted to separate tripods and placed at the workstation in a way that would be representative of the usual position of the subject. Although ISO 7726:2001 [23] recommends placing probes at 0.60 m from floor level (for a seated person when only one measurement is made), this study accepts the recommendation made by ASHRAE 55-2013 [8] in relation to placing the probes above desktop level when strong radiant sources (i.e. PCs) are blocked by furniture. For this reason, all the measurements were made at 0.90 m from floor level.

Further, it is noteworthy that although the ATP Hot Wire Anemometer is not omnidirectional, both ISO 7726:2001 and ASHRAE 113-2009 allow the use of a '*directionally sensitive anemometer* […] *if it is carefully oriented to indicate the true air speed at any test position*' [24]. A smoke test using an incense stick was carried out at every workstation to identify the main direction of the air flow prior to each measurement.

Calculation of the Predicted Mean Vote (PMV) for each set of data was done in Microsoft Excel with a Visual Basic macro routine written according to the computer programme presented in Annex D of ISO 7730:2005. The PPD indices were obtained from the PMV indices [2].

Measurements from the closest weather data station, El Bosque, were used for identifying the outdoor air temperature. Outdoor air temperatures ranged from a minimum of 13.7°C (9th of August at 10:00 am during the survey in Cll 100-MM) to a maximum of 19°C (5th August at 4:00 pm during the survey in Cll 93-MV), which represent the general trend of cooler mornings and warmer afternoons.

2.6 Estimation of clothing insulation and metabolic rate

Using the collected data on clothing ensembles, the overall clo value for each subject was obtained by the summation of the partial insulation values of each garment reported according to tables provided in ISO 9920:2009 [25]. Additionally, the insulating effect of the chair was brought into consideration by applying the 0.15 clo estimation made by Cena and de Dear [22] for similar types of chairs. Even though this approach is the most widely used, it relies on the subjective understanding that occupants have of the weight of their pieces of clothing, or even where a specific garment should be reported. This study found values (without considering insulation from the chair) between 0.26 clo and 1.48 clo. Although the final average values in each office accord to the expectations (0.94 clo, 0.81 clo and 0.80 clo), the extremes could indicate errors in these data. For example, a clo of 0.3 would be equivalent to an ensemble of bra and pants plus t-shirt, shorts, light socks, sandals; and a clo of 1.4 would represent an ensemble of underwear (short sleeves/legs) plus boiler suit, insulated jacket and trousers, socks, shoes [26]. It would seem unlikely – though not impossible – that both ensembles would be recorded within the same working environment and weather conditions. Possible sources of errors could be errors during data entry or due to inaccurate self-reporting by the participants. Therefore, even though most clo values are estimates and errors of up to 20% are expected in the estimation of typical ensembles [26] any significant outliers in our analyses are discounted.

The description of the activity level during the last hour was converted into met units by applying the tables provided in the standards (ASHRAE 55-2013 [8], ISO 7730:2005 [2], ISO 8996:2004 [27]). Following the approach of Rowe [28], weighting factors were applied to those activities according to their time band: 50% for activities during the last 10 minutes, 25% for those in the preceding 10 minutes, 15% for those in the 10-minutes lapse before that and finally 10% for the previous half an hour. Similarly, adjustments were made according to previous food/beverage intake (last 15 minutes): 5% added for beverages or cigarette, while 10% for snacks or meals. Average metabolic rates in the surveyed offices were close (1.33 met, 1.35 met and 1.30 met). Although these values are in the upper region of a sedentary activity, they represented correctly the general level of activity of these offices, which had an operation linked directly with the sales force.

3. Results and discussion

3.1 Thermal sensation votes vs. PMV

In this section, standard predicted values and comfort ranges (ISO 7730:2005, ANSI/ASHRAE Standard 55:2013 and EN Standard 15251) are compared with actual comfort votes gathered in the survey. The first comparison is between the model-obtained PMVs and the questionnaire-recorded Thermal Sensation Votes (TSVs). Figure 4 shows box plots of PMVs and TSVs for the three offices. Looking at the means (i.e. the diamonds within the boxes), the PMV model successfully predicts that the mean thermal perception in Cll 93-MV and Cll 100-MM is between -0.5 and 0.5 (i.e. neutral). Regarding Cll 72-NV, it also places this office within that range, which demonstrates that it fails to predict that the real mean thermal sensation is ‘slightly cool’ (i.e. -1). From the boxplot of the vote distributions (Figure 4) it can be seen that ISO predicted PMVs do not approximate the actual thermal vote distributions in the three offices since the PMV model underestimates the actual discomfort, especially for the naturally ventilated environment. This points to a better capability of the model in predicting average perception than voting distribution.

From the boxplot of the predicted and actual votes distributions for Cll 72-NV it can be noticed that the actual votes range from 1 to -3 while the predicted ones range from 1 to -1. As a consequence, the mean PMV overestimates by 1 scale point the actual mean “slightly cold” thermal sensation recorded in the natural ventilated office.

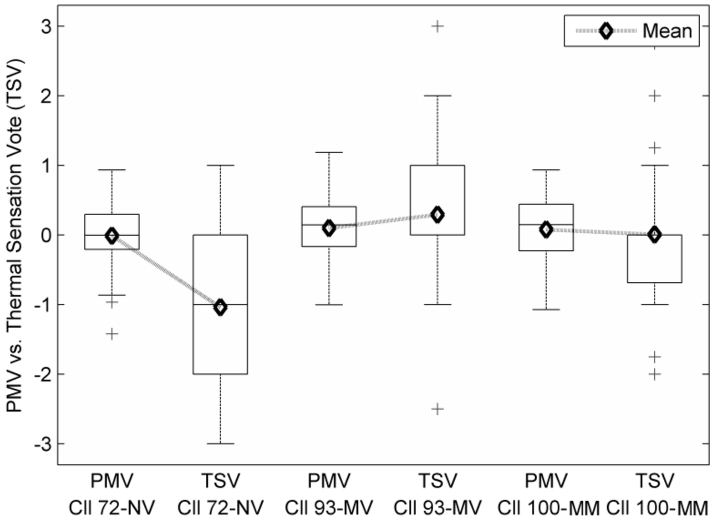


Figure 4 Box plot of PMV and TSV votes for the three office buildings (NV, MV and MM). The line within each box is the median, the diamond is the mean, the edges of the box are the 25th and 75th percentiles (indicated as q1 and q3 respectively), the thin lines (whiskers) extend to those values between q3 - 1.5(q3 – q1) and q1 + 1.5*(q3 – q1), and values outside this range (outliers) are plotted individually as crosses.*

The mean of the PMVs for Cll 93-MV and Cll 100-MM is around 0.1, while for Cll 72-NV is - 0.01, these values correspond to a mean PPD of 8.9%, 10.4% and 10.2% for Cll 72-NV, Cll 93-MV and Cll 100-MM respectively (Table 3). This means that, according to the ISO predictions, about 90% of the occupants are thermally comfortable in the three offices. This value can be compared with the percentage of occupants who gave thermal votes between -1 and 1[1], i.e. 62%, 85% and 80% for Cll 72-NV, Cll 93-MV and Cll 100-MM respectively (Table 3). This comparison confirms that the ISO PMV model underestimates the actual discomfort in the case of the naturally ventilated office.

Table 3 Statistical summary of PMV and PPD indices and Thermal Sensation Votes (TSV)

	Cll 72-NV	**Cll 93-MV**	**Cll 100-MM**
Number of sets[2]	*39*	*34*	*35*
Mean PMV	-0.01	0.1	0.08
Mean PPD	8.9%	10.4%	10.2%
Mean TSV	-1.04	0.3	0.01
-1≤TSV≤+1	62%	85%	80%

If the 80% acceptability criterion were used, i.e. declaring a thermal environment as comfortable when 80% of occupants are feeling between ‘slightly cool’ (PMV=-1) and ‘slightly warm’ (PMV=+1) (ISO 7730:2005), the PMV model would predict that all the surveyed offices in Bogota be regarded by their occupants as thermally comfortable. However, applying the same criteria for the observed TSVs there is agreement with the PMV prediction only for Cll 93-MV and Cll 100-MM (85% and 80% of their occupants within the

[1] According to the responses to the second question of the questionnaire, 98% of the comfort votes (people describing their thermal environments as ‘comfortable’) belong to subjects that described their thermal perception between ‘slightly cool’ and ‘slightly warm’, confirming the choice of a comfort range for TSV between -1 and 1.
[2] The sample for the PMV calculation was reduced because of the lack of realistic information about six clothing ensembles. Additionally, one set of data was excluded because its air speed (1.24 m/s) was above the limit accepted for using this index (0 m/s to 1 m/s).

reference band), while Cll 72-NV clearly does not meet the criterion (62%). As already noted above, this difference is due to the PMV underestimation of the votes on the cool side (i.e. “slightly cool”, “cool” and “cold”) encountered in the naturally ventilated office.

Table 4 Distribution of PMV values

PMV	-3	-2	-1	0	1	2	3
Cll 72-NV	0%	0%	13%	80%	8%	0%	0%
Cll 93-MV	0%	0%	14%	68%	19%	0%	0%
Cll 100-MM	0%	0%	13%	68%	18%	0%	0%
Overall	0%	0%	13%	72%	15%	0%	0%

This underestimation of the model has already been noted in other studies [29] but it contrasts with the literature where it is commonly observed that the PMV model mostly overestimates warm and cold sensations in naturally ventilated buildings [12] [30]. In this regard two main facts need to be pointed out:

- the extreme TSV points in the NV office were measured from 9:30 am to 10:30 am, at a time where the occupants had just entered the building which was in the process of warming up;
- Cll 72-NV had the biggest proportion (65%) of subjects reporting unavailability of personal control (*i.e.* no control, see Table 5). In fact, natural ventilation in Cll 72-NV is mainly given by grates placed above the windows which cannot be easily controlled by the occupants since some of them are permanently open.

Taking into account those facts, the extreme votes could therefore be related to the mutual influence of two aspects:

- the lower initial temperatures of the office in the process of warming up;
- the higher expectations of occupants who had just arrived in the office which could not be met by any control available (the entrance of early-morning cold air in the office could not be avoided by closing the grates).

Despite the fact that the PMV model includes some adaptation factors such as the possibility of adjusting clothing, it does not take into account of other more complex psychological aspects which can drive the judgement of a thermal environment. In this case, some unexpected factors for a natural ventilated office such as high thermal expectation and low personal control (i.e. the occupants’ inability to control the ventilation grates) could be considered responsible for the inadequacy of the model. This demonstrates that the PMV model fails in predicting conditions for naturally ventilated buildings when occupants’ expectations are very high (higher than those normally experienced in climate chambers). It also provides powerful support for the requirement in the adaptive comfort standards that occupants of naturally ventilated buildings must be able to control the ventilation by manipulating openings [8].

Relative humidity in the surveyed offices was found to be within a reduced range: 30% to 44%. These figures show that relative humidity was at a level regarded as ‘normal’, and within the limits recommended by ASHRAE [8].

3.2 Thermal sensation votes vs. Adaptive models

Apart from the comfort criteria based on the heat-balance approach, ASHRAE 55-2013 does incorporate a method based on the adaptive approach to thermal comfort. According to this standard, when the main ventilation strategy of a building is naturally-driven i.e. without mechanical cooling installed (this definition excludes the MM buildings in the free-running

category) and occupant-controlled, two sets of operative temperature limits based on the prevailing mean outdoor air temperature can be used to establish the ranges of operative comfort temperatures for 80% and 90% acceptability. The monthly mean outdoor temperature during the survey period is equal to 14°C. The corresponding temperature limits which can be derived from the ASHRAE adaptive relation (Figure 1) are equal to 18.6 °C and 25.6 °C for the 80% acceptability limits.
Also the EN Standard 15251 includes a method for calculating the range of acceptable summer indoor temperatures for free-running buildings where occupants are able to access openable windows and are free to change clothing (this definition includes MM buildings in the free-running category). The temperature limits associated with a monthly mean outdoor temperature of 14 °C are equal to 19.42 °C and 27.42 °C for 85% acceptability (PPD < 15%).
ASHRAE and EN Standard 15251 limits are plotted in Figure 5 together with the limits given by the new relation developed by Humphreys correlating neutral temperatures with prevailing mean outdoor temperatures [31].
Box plots of operative temperatures To and comfort operative temperatures ComTo are also shown in Figure 5. Comfort operative temperatures are those temperatures which correspond to thermal votes between -1 and 1 on the perception scale (i.e. central neutral category). As noted earlier, for the MV and MM office 85% and 80 % of the votes are within the central neutral category, while for the NV office only 62 % of the votes are within it.

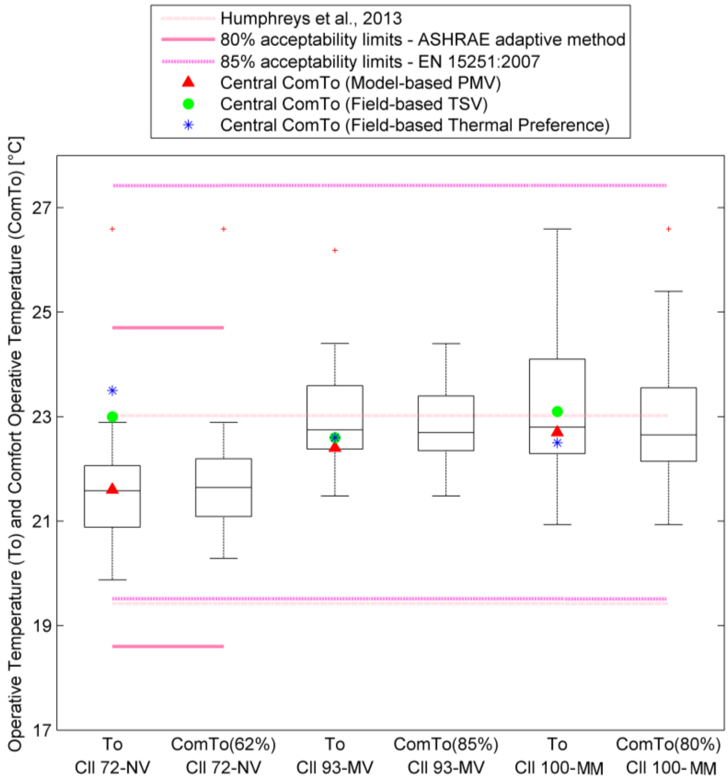


Figure 5 Comparison of comfort temperature ranges for NV, MV and MM. Box plot of To and ComTo for the three office buildings (NV, MV and MM). The line within each box is the median, the edges of the box are the 25th and 75th percentiles (indicated respectively as q1 and q3), the thin lines (whiskers) extend to those values between q3 - 1.5(q3 – q1) and q1 + 1.5*(q3 – q1), and values outside this range (outliers) are plotted individually as red crosses.*

All the operative temperatures for the NV office are within the ASHRAE adaptive range of 80% acceptability and the EN adaptive range of 85% satisfaction (see Figure 5); however, only 62% of the occupants found the NV environment comfortable. Therefore the ASHRAE and EN adaptive methods underestimate the discomfort in the naturally ventilated office. This

is further evidence of the impact of the availability of personal control (i.e. inoperable ventilation grates) in Cll 72-NV compared to what is normally experienced in natural-ventilated environments. This fact lessens the adaptation possibilities of the occupants and causes the inadequacy of the adaptive relations.
The 85% acceptability range from the EN Standard 15251 is good at approximating the level of comfort in Cll 93-MV (85%), but it fails in predicting the level of acceptance in Cll 100-MM (80%) and Cll 72-NV (62%).

From the boxplot of the temperature distributions in Figure 5 it can be further noted that Cll 100-MM has the largest range of operative and comfort temperatures (a 5°C temperature band ranging from 21°C up to about 26°C), while the naturally ventilated building has the narrowest range (only 3°C temperature band from 20°C to 23°C). This is in disagreement with many field studies in which people in naturally ventilated environments are found to accept a wider range of temperatures. This also contrasts with the expectation that the air-conditioned office should provide a tighter control over thermal conditions [12]. The large temperature range in Cll 100-MM is due to a managerial decision over the setting conditions of the AC system, rather than to a poor design of the system (i.e. a design based on an underestimation of the heat load). In the air-conditioned office the temperature for the activation of the cooling unit is set very high (27°C) and occupants can open the windows when the AC is off (mixed-mode operation), therefore temperatures are allowed to vary much more than in a conventional strictly controlled air-conditioned environment. Despite the large temperature variation, the PMV model (which is derived from climate chamber experiments where environmental conditions are almost constant, i.e. steady-state variations) gives reliable predictions. This is due to the fact that, despite running in free-mode, the office has a reduced number of openable windows (see Section 3.3) and, therefore, occupants' perceived control is comparable to that experienced in air-conditioned environments where, notoriously, occupants have low personal control.

3.3 Occupants' use of adaptive controls

Occupants had five different options to choose from when asked about their level of control (no control, light control, medium control, high control, total control). Overall, 47% of them declared to have no control over the thermal conditions of their workplace, and around the same proportion described it as 'Low' or 'Moderate'. In terms of offices, Cll 72-NV had the biggest proportion of subjects reporting unavailability of personal control (65%), followed by Cll 100-MM (50%), while only 24% of occupants shared that level in Cll 93-MV. Overall, a 'High' or 'Total' level of control was not widely accessible (9% overall), which is not a surprise in buildings that have mechanical ventilation or air conditioning as their main ventilation strategy. However, in the mixed-mode free running office and in the naturally ventilated office the level of perceived control is lower than is normally experienced.

Table 5 Distribution of level of control

	No control	Low	Moderate	High	Total
Overall	47%	21%	23%	5%	4%
Cll 72-NV	65%	8%	20%	5%	3%
Cll 93-MV	24%	30%	27%	8%	11%
Cll 100-MM	50%	26%	21%	3%	0%

Different control strategies were suggested in the questionnaire in order to establish whether they were present and, if so, how often were they used. These strategies involved operating or adjusting windows, exterior doors, interior doors, thermostats, blinds or drapes, local heaters or local fans. Table 6 presents a summary of existing strategies in each office. This table was generated taking into account answers only from those who selected a level of control between 'Low' and 'Total' (i.e. excluding those from occupants who reported 'No control'). Besides this, answers were divided into 'Present/Used' (strategy is present and is used) and 'Not present/Not used' (strategy is not present or it is present but is not used). The most common control strategies found were operation of windows and adjustment of blinds or drapes (41% and 46% respectively). On the other hand, the least used were operation of a thermostat and switching on/off a local heater (2% and 3% respectively). From Table 6 it is clear that there is a reduced existence/operation of openable windows for the mixed-mode free running office and the naturally ventilated office.

Table 6 Occupants' use of adaptive controls

		Window	Exterior door	Interior door	Thermostat	Drape /blind	Heating	Fan
Overall	P/U	41%	19%	18%	2%	46%	3%	8%
	Not P/U	59%	81%	82%	98%	54%	97%	92%
Cll 72-NV	P/U	25%	28%	20%	3%	38%	5%	5%
	Not P/U	75%	73%	80%	98%	63%	95%	95%
Cll 93-MV	P/U	59%	16%	19%	0%	49%	0%	11%
	Not P/U	41%	84%	81%	100%	51%	100%	89%
Cll 100-MM	P/U	39%	13%	16%	3%	53%	5%	8%
	Not P/U	61%	87%	84%	97%	47%	95%	92%

P/U= Present/Used, Not P/U=Not Present/Not Used

3.4 Compliance of the neutral temperatures with the standards

It is not enough to describe an existing environment as comfortable or uncomfortable. By means of regression of collected or calculated data it is possible to obtain the temperature at which the subjects in the study are thermally neutral (i.e. they would have selected 'Neither hot nor cold' in the questionnaire). In Table 7 and Figure 5 different central comfort temperatures Central ComTo (i.e. neutral temperatures) are reported; they represent the results of different regression analysis:

- Central ComTo (Model-based PMV): it is based on the regression of mean PMV binned in 0.5 To intervals. Central ComTo happens when PMV=0 (see Figure 6, Figure 7 and Figure 8).
- Central ComTo (Field-based TSV): the same method used in (1) but based on TSV (see Figure 6, Figure 7 and Figure 8).
- Central ComTo (Field-based Thermal Preference): regression of mean Preference Votes binned in 0.5 To intervals. Preferred operative temperature ComTo happens when the regression line intersects the 0 (no change) Preference Vote.

Table 7 Central comfort temperatures ComTo in the three offices as calculated by the three different methods illustrated above

	Cll 72-NV	Cll 93-MV	Cll 100-MM
Central ComTo (Model-based PMV)	21.6°C	22.4°C	22.7°C
Central ComTo (Field-based TSV)	23°C	22.6°C	23.1°C
Central ComTo (Field-based Thermal Preference)	23.5°C	22.6°C	22.5°C

Table 7 suggests that the estimated values of the neutral operative temperatures for Cll 93-MV and Cll 100-MM are quite similar in the three different methods and they approximate the median of the distributions of To fairly well (see Figure 5). This vicinity with the median is explained by the high percentage of comfortable occupants in Cll 93-MV and Cll 100-MM. However, for the NV office the situation is slightly different: the estimation based on PMV is the one giving the best approximation of the median of the box plot, while values based on TSV and Thermal Preference Votes are much higher, around 23°C. This difference reveals the inability of PMV to predict neutral temperatures for the NV office.
Neutral temperatures for the three offices are quite similar around 23°C; therefore the natural ventilated office does not imply lower neutral temperatures; this is a further confirmation of the higher thermal expectations in CII 72-NV compared to conventional natural ventilated environments. The MM office has the largest range of operative and comfort temperatures, while the NV office has the narrowest range. This is due the particular setting conditions of the AC system as seen before (see Section 3.2).

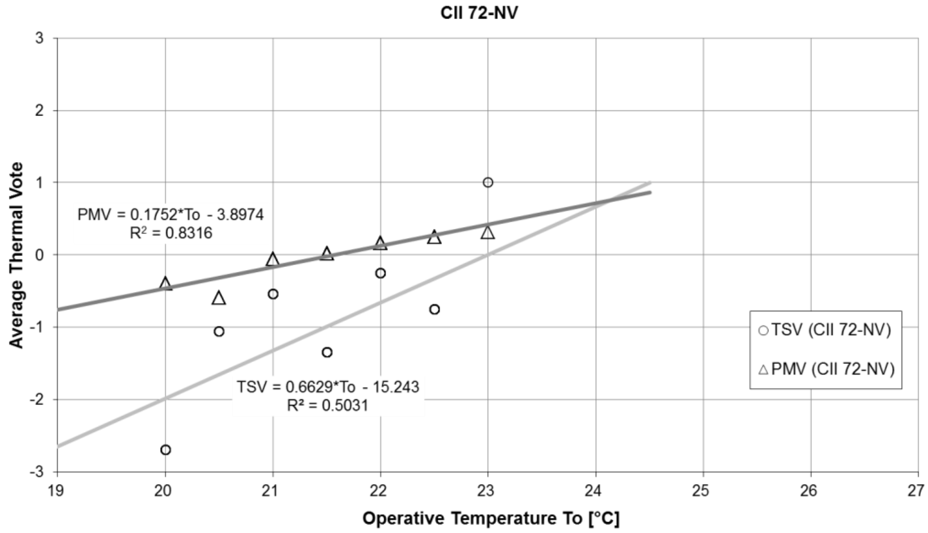


Figure 6 Linear regressions of PMV and TSV vs. Operative Temperature for CII 72-NV

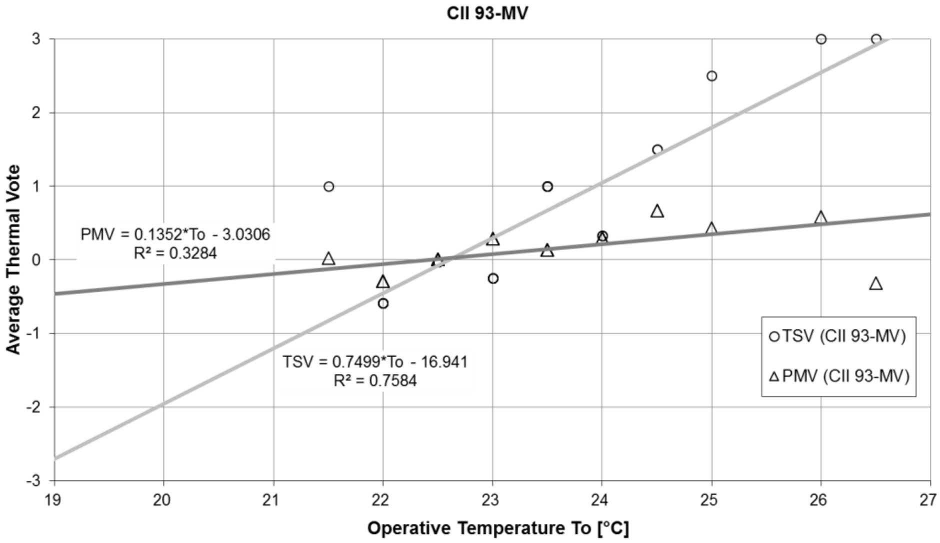


Figure 7 Linear regressions of PMV and TSV vs. Operative Temperature for CII 93-MV

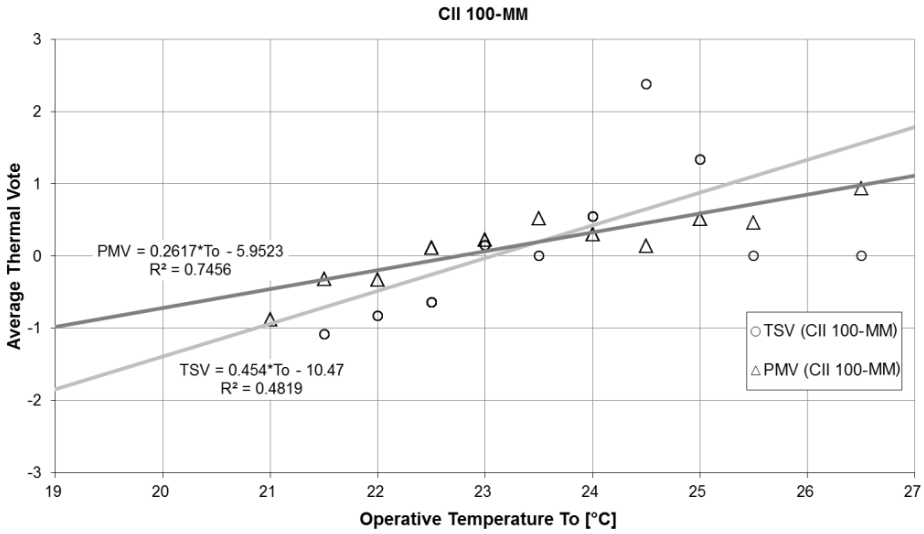


Figure 8 Linear regressions of PMV and TSV vs. Operative Temperature for CII 100-MM

4. General discussion of the findings

The findings can be easier understood looking at the simplified qualitative plot of Figure 9 which shows three possible level of occupants' expectations (Low, Medium, High in the y-axis) and three possible degrees of occupant's control (Low, Medium, High in the x-axis). The PMV/PPD derives from climate chamber studies which are characterized by low control and medium expectations (yellow area). The EN Standard 15251 adaptive model derives from field studies in natural ventilated and mixed buildings characterized by medium/high control and low/medium expectations (green area). The three black symbols represent the three surveyed buildings: Cll 72-NV (star, high expectations and very low control), Cll 100-

MM (circle, medium/high expectations and low control), Cll 93-MV (triangle, medium expectations and low/medium control).

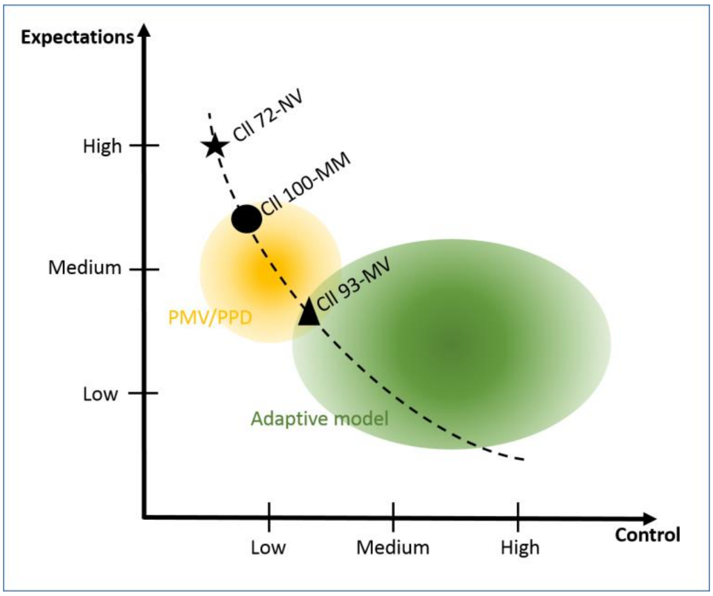


Figure 9 Degrees of occupants' expectations and control in the three surveyed offices

ISO-7730 PMV model is able to estimate the mean thermal perception in the mechanically-ventilated and in the mixed-mode free-running office (circle and triangle inside the yellow area), but it fails to predict that the mean thermal sensation in the naturally ventilated office is 'Slightly cool' (star outside the yellow area). The above result is due to the lack of control in the naturally ventilated office (i.e. inoperable ventilation grates) which exacerbate occupant's expectations. Also, the PMV model is successful at estimating the neutral operative temperature for the mechanical-ventilated and the mixed-mode free-running office, but not for the naturally ventilated one.

The EN Standard 15251 adaptive relation is able to model thermal comfort conditions in the mechanical-ventilated office (triangle inside the green area) but is found to underestimate the discomfort in the mixed-mode free-running office and in the naturally ventilated one (circle and star outside the green area). This can be explained by the reduced availability of personal control in the two offices, which lessens the adaptation possibilities of the occupants.

5. Conclusions

ISO-7730 predicted values and ASHRAE-55 and EN Standard 15251 comfort temperature bands have been compared with actual physical data and comfort votes gathered in a field study in Bogota, Colombia consisting of three offices having different ventilation regimes (natural forces NV, mechanical ventilation MV and mixed-mode MM i.e. both natural ventilation and air-conditioning). Our findings show that the PMV and adaptive model incorporated in the ASHRAE standard (which is the standard currently adopted in Colombia for regulating indoor environmental parameters) is able to predict mean thermal perception in mechanically-ventilated environments in Bogota. This conclusion could also be extended to other cities under the same subtropical highland climate. However, we cannot draw similar conclusions regarding the applicability of the EN and ASHRAE adaptive models to naturally ventilated and mixed-mode free-running buildings since the reduced availability of personal control over the windows in the two surveyed offices invalidates model predictions. More

field studies in NV and MM offices are needed to verify the applicability of the EN and ASHRAE adaptive relations.
From the findings it also emerges that the applicability of PMV/PPD and adaptive models is closely dependent to the possibility of controlling the windows given to the occupants. Therefore a classification of spaces based on the level of windows control is more realistic than only considering the presence of an AC unit. For example, we showed that the PMV model is able to predict comfort conditions in the MM free-running office where the low level of occupants' perceived control is comparable to that experienced in air-conditioned environments.

6. Acknowledgements

We would like to thank the offices that participated in the study for their cooperation.

7. References

1. De Dear, R., *Thermal comfort in practice.* Indoor Air, 2004. **14**: p. 32-39.
2. ISO, *Ergonomics of the thermal environment — Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria (ISO 7730-2005)*. 2005.
3. Van Hoof, J., *Forty years of Fanger's model of thermal comfort: comfort for all?* Indoor Air, 2008. **18**(3): p. 182-201.
4. Fanger, P.O., *Thermal Comfort*. 1970, Copenhagen: Danish Technical Press.
5. Nicol, J.F. and M.A. Humphreys, *Thermal comfort as part of a self-regulating system.* Building Research and Practice, 1973. **1**(3): p. 174-179.
6. de Dear, R.J. and G.S. Brager. *Developing an adaptive model of thermal comfort and preference*. in *ASHRAE Transactions*. 1998.
7. Nicol, F. and M. Humphreys, *Derivation of the adaptive equations for thermal comfort in free-running buildings in European standard EN15251.* Building and Environment, 2010. **45**(1): p. 11-17.
8. ASHRAE, *ANSI/ASHRAE Standard 55-2013, Thermal environmental conditions for human occupancy*. 2013: Atlanta, Ga.
9. 15251:2007, E., *Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics (EN 15251:2007).* 2007.
10. Kottek, M., Grieser, J. , Beck, C., Rudolf, B. and Rubel, F., *World Map of the Köppen-Geiger climate classification updated.* Meteorologische Zeitschrift, 2006. **15**(3): p. 259-263.
11. IDEAM, *Atlas climatológico de Colombia*. 2005: Colombia.
12. Moujalled, B., R. Cantin, and G. Guarracino, *Comparison of thermal comfort algorithms in naturally ventilated office buildings.* Energy and Buildings, 2008. **40**(12): p. 2215-2223.
13. Ricciardi, P. and C. Buratti, *Thermal comfort in open plan offices in northern Italy: An adaptive approach.* Building and Environment, 2012. **56**: p. 314-320.
14. Indraganti, M., R. Ooka, and H.B. Rijal, *Thermal comfort in offices in summer: Findings from a field study under the 'setsuden' conditions in Tokyo, Japan.* Building and Environment, 2013. **61**: p. 114-132.
15. Djongyang, N. and R. Tchinda, *An investigation into thermal comfort and residential thermal environment in an intertropical sub-Saharan Africa region: Field study report during the Harmattan season in Cameroon.* Energy Conversion and Management, 2010. **51**(7): p. 1391-1397.
16. Djongyang, N., R. Tchinda, and D. Njomo, *Thermal comfort: A review paper.* Renewable and Sustainable Energy Reviews, 2010. **14**(9): p. 2626-2640.
17. MAVDT, *REGLAMENTO COLOMBIANO DE CONSTRUCCIÓN SISMO RESISTENTE*. 2010.
18. ICONTEC, *NORMA TÉCNICA COLOMBIANA 5316: CONDICIONES AMBIENTALES TÉRMICAS DE INMUEBLES PARA PERSONA*. 2004.
19. Luo, M., et al., *Evaluating thermal comfort in mixed-mode buildings: A field study in a subtropical climate.* Building and Environment, 2015. **88**: p. 46-54.
20. IDEAM, *Segunda comunicación nacional ante la Convención Marco de las Naciones Unidas sobre Cambio Climático*. 2010: Bogotá.
21. Vicario, P., *World air conditioning Colombia - A multi client study*. March 2014, BSRIA.

22. Cena, K., de Dear, R., *Field study of occupant comfort and office thermal environments in a hot-arid climate*. 1988, FINAL REPORT ASHRAE RP-921.
23. ISO, *Ergonomics of the thermal environment — Instruments for measuring physical quantities (EN ISO 7726:2001)*. 2001.
24. ASHRAE, *Method of Testing for Room Air Diffusion (Standard 113-2009)*. 2009.
25. ISO, *Ergonomics of the thermal environment – Estimation of thermal insulation and water vapour resistance of a clothing ensemble (ISO 9920:2009).* 2009.
26. Butcher, K. and E. Chartered Institution of Building Services, *Environmental design : CIBSE guide A*. [7th ed.]. ed, ed. K. Butcher and E. Chartered Institution of Building Services. 2006, London: London : Chartered Institution of Building Services Engineers.
27. ISO, *Ergonomics of the thermal environment -- Determination of metabolic rate (ISO 8996:2004)*. 2004.
28. Rowe, D.M., *Activity rates and thermal comfort of office occupants in Sydney.* Journal of Thermal Biology, 2001. **26**(4–5): p. 415-418.
29. Barlow, S. and D. Fiala, *Occupant comfort in UK offices—How adaptive comfort theories might influence future low energy office refurbishment strategies.* Energy and Buildings, 2007. **39**(7): p. 837-846.
30. Mishra, A.K. and M. Ramgopal, *Field studies on human thermal comfort — An overview.* Building and Environment, 2013. **64**: p. 94-106.
31. Humphreys, M.A., H.B. Rijal, and J.F. Nicol, *Updating the adaptive relation between climate and comfort indoors; new insights and an extended database.* Building and Environment, 2013. **63**: p. 40-55.